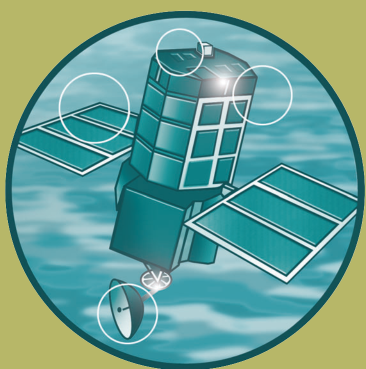
Joint Defra/EA Flood and Coastal Erosion
Risk Management R&D Programme

Spatial-temporal rainfall modelling with climate change scenarios

R&D Technical Report FD2113/TR



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Spatial-temporal rainfall modelling with climate change scenarios

R&D Technical Report FD2113/TR

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Statement of use
This technical report presents methodological developments for generating artificial rainfall sequences that are suitable for flood risk assessment and management. Input from climate models allows representation of changes in future rainfall, expressed as shifts in probability distributions. This report will be of use to those involved in future flood mitigation.

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Executive summary

DEFRA has five strategic priorities. One of these is climate change, for which a target outcome is to manage risk from flooding and coastal erosion in a way that furthers sustainable development (see http://www.defra.gov.uk/corporate/what-do-we-do/climate.htm). This project provided tools to assist in achieving this. The overall aim was to develop methods for the generation of artificial rainfall data incorporating scenarios of future climate change, for any location in England and Wales. Such artificial data can be used to drive simulations of catchment processes over extended time periods. The results can be used to assess, for example, likely changes in flood risk, the effectiveness of potential strategies for risk management, or the impacts of potential changes in land use. This approach to risk assessment and management is called 'continuous simulation'. It is data intensive: most catchments in the UK are small enough to respond to relatively localised rainfall events, and therefore rainfall data are required at high space and time resolution, for example at individual spatial locations and at daily or hourly time scales.

Prior to the present project, continuous simulation methodologies were developed in two other DEFRA-funded projects. Under project FD2106, carried out at CEH Wallingford, continuous simulation rainfall-runoff models were developed to represent catchment flood response to rainfall inputs; and in project FD2105, carried out jointly between Imperial College, UCL and CEH Wallingford, regionally-applicable methods for the continuous simulation of rainfall and evaporation, required as input to the rainfall-runoff models, were developed. The present project built upon the work carried out in FD2105, enhancing the methods there to enable climate change scenarios to be incorporated.

Most of our understanding of the climate system is based on deterministic models of the physical and chemical processes involved. However, despite continuing improvements in these climate models, there are at present questions regarding their ability to represent rainfall adequately at the fine space and time scales required. This project therefore sought to generate rainfall sequences by exploiting statistical relationships between rainfall and other variables that are better represented in climate models. For UK applications, a recommendation is that the most useful variables for this purpose are temperature, sea level pressure and relative humidity.

A further difficulty is that future projections can vary substantially between different climate models. For example, this project found that the Hadley Centre's HadCM3 model projects a much greater decrease in relative humidity over the next century than does the Australian model CSIROMk2; as a result, rainfall simulations driven by HadCM3 tend to be much drier than those based on CSIROMk2. It is increasingly being recognised that more than one climate model should be used to evaluate future climate scenarios, and that climate model uncertainty should be recognised and accounted for in any prudent analysis. In this project, we have proposed and tested a novel strategy for achieving this, in which climate model uncertainty is represented explicitly via probability distributions.

The main achievements of the project are as follows:

1. The daily rainfall simulation methodology from project FD2105 has been used to generate daily rainfall sequences incorporating climate change scenarios. This is done by exploiting relationships between rainfall and large-scale atmospheric conditions. The methodology has been tested extensively. The simulated sequences have realistic properties, and the projected changes in future UK rainfall agree in qualitative terms with those obtained by other means (for example, using climate model rainfall outputs directly). For example, in south-east England, the simulations suggest a tendency for summers to become drier and winters wetter under the SRES A2 greenhouse gas emissions scenario (which underpins many climate change 'headlines'). However, there is considerable year-to-year variability in seasonal rainfall and it would be overly simplistic to conclude that all summers will become drier and all winters wetter. A key feature of the methodology used here is that the changes are represented as shifts in probability distributions. Graphical displays of these distributions provide a clear picture of the magnitude of the projected changes, relative to year-on-year variability.

2. Stable relationships, valid under a wide range of conditions, have been found to exist between properties of rainfall at different time scales. These enable properties of hourly rainfall to be reconstructed surprisingly accurately at any location in England and Wales, given only daily information such as that from (1) above. In turn, the reconstructed properties can be used to deduce the parameters of the hourly rainfall model recommended in FD2105. This provides a means of generating hourly sequences incorporating the effects of climate change. Since the parameters of the hourly model correspond to key features of the rainfall process (e.g. the arrival rate of storms), this work also provides insights into how these features may change in the future. An important conclusion is that in England, under the SRES A2 emissions scenario, the changes identified in (1) above are associated with increases in storm frequencies in winter but decreases in summer. However, the intensity of rainfall within storms is likely to increase throughout the year. The combination of these two changes could lead to increased risk of both floods and droughts.

3. It has been demonstrated that multi-site sequences of hourly rainfall, incorporating climate change scenarios, can also be generated, using daily rainfall sequences from (1) above in conjunction with the multi-site disaggregation methodology developed in FD2105.

4. An investigation has been carried out into the sensitivity of results to the choice of climate model used to provide large-scale atmospheric conditions in (1) above. It was found that this choice may affect the results substantially. Climate model uncertainty should therefore be considered in any prudent analysis of future risk.

5. A pilot methodology has been developed for combining the outputs from several climate models in a coherent and interpretable manner, thereby enabling climate model uncertainty to be accounted for in the generation of rainfall sequences. This task was technically challenging, however, and therefore the methodology has not been developed as extensively as other aspects of the project.

6. An investigation has been carried out into the ability of regional climate models (RCMs) to represent properties of daily rainfall sequences directly for risk management purposes. The conclusion was that an individual RCM cannot be relied upon to reproduce rainfall properties particularly well; however, an ensemble of RCMs can be used to obtain a distribution of rainfall properties which is more or less consistent with observations.

The overall task of using climate model outputs to generate subdaily rainfall sequences has been split into several distinct sub-tasks. These are as follows:

1. Use the pilot methodology for combining climate model outputs, to generate a large number of alternative sequences of large-scale atmospheric variables over the time period of interest.

2. For each atmospheric variable sequence:
   - Generate a large number of daily rainfall sequences using the daily rainfall simulation methodology.
   - For each month of the simulation period, calculate selected statistical properties of the simulated daily rainfalls, and use the relationships between rainfall properties at different timescales to reconstruct the corresponding hourly properties
   - Use the FD2105 single-site methodology and software to fit a separate hourly rainfall simulation model for each month of the simulation period
   - Use the fitted hourly models to generate as many hourly sequences as required.

The result of this process will be a large number of subdaily sequences. The variation between these sequences represents uncertainty due to climate models, to the inexact relationship between rainfall and large-scale atmospheric variables and to day-to-day variation in real rainfall sequences.

The division into sub-tasks makes the methodology here suitable for a ‘pick-and-choose’ approach: for example, in situations where subdaily data are not required, one can stop after the daily sequences have been generated. Furthermore, if a practitioner has their own preferred method for carrying out one of the steps above, they are free to use it.

Several opportunities for further research arise out of this project. The most important are as follows:

1. To develop further the pilot methodology for combining climate model outputs, and in particular to produce a user-friendly software implementation that is suitable for general use.

2. To verify the scaling relationships between rainfall properties at different time scales using an extended rainfall data set. In this project, the relationships have been tested using data from about a dozen gauges representing a variety of rainfall

regimes across England and Wales. A national verification exercise would, however, enhance their credibility.

3. To develop further the daily rainfall simulation model, in order to relax some constraints that currently lead to a slight underestimation of extreme summer rainfalls.

4. To improve the accessibility of some of the techniques that have been developed, by connecting some of the software tools so as to reduce the need for manual intervention when implementing the methodology.

Contents

1. Introduction

A principal aim of the DEFRA Broad-Scale Modelling (BSM) thematic area was to provide decision-support systems for strategic assessment of flood risk and management. This has now been taken forward within the revised DEFRA / EA Research and Development thematic structure, particularly in the Modelling and Risk (MAR) theme. Strategic assessment demands consideration of the impacts of changes in climate and land use. In project FD2106, continuous simulation rainfall-runoff models were developed to represent catchment flood response and, in project FD2105, regionally-applicable methods for the continuous simulation of rainfall and evaporation, required as input to the rainfall-runoff models, were developed.

The present project extends the methods from FD2105 to represent scenarios of climate change. This is achieved by linking these methods with the outputs from the latest numerical climate models, to provide inputs to catchment rainfall-runoff models at appropriate temporal scales for flood estimation. Both general circulation models (GCMs) and regional climate models (RCMs) are considered. GCMs provide climate simulations on a coarse grid (with typical resolution around 250×250km^2 at UK latitudes) over the entire globe; RCMs operate on a finer grid resolution (typically around 50×50km^2) over smaller areas, for example Europe. RCM simulations are usually used to add detail to a GCM simulation over an area of interest; RCMs can therefore be regarded as a physically-based means of adding detail to GCM outputs.

To assess the impact of potential climate change upon flood frequency and magnitude and upon low flow periods, the output from climate models must be converted to scales that are appropriate for input to hydrological models. Most catchments in the UK are small enough to respond to relatively localised rainfall events, so rainfall data are typically required at daily to hourly or sub-hourly time scales. Assessment of catchments ranging in area from a few km^2 to a few hundred km^2 or larger is needed, with appropriate representation of rainfall variability; hence rainfall data may be required on spatial scales as fine as a few km^2. The process of enhancing the spatial and temporal resolution of climate model outputs is commonly referred to as *downscaling*.

Although climate models represent our best available understanding of climate system dynamics (IPCC, 2001), it is widely accepted (e.g. Jenkins and Lowe, 2003) that different models can give rather different projections of future climate. The need to account for model error is increasingly being recognized (e.g. Senior, 2002), and this has resulted in a shift towards probabilistic climate forecasting (Allen and Stainforth 2002; Giorgi and Mearns 2002). A number of articles (e.g. Wigley and Raper 2001; Allen *et al*. 2000 and Lopez *et al*. 2006) have discussed methods for the probabilistic estimation of global-mean warming. However, the current project makes use of monthly time series of several atmospheric variables, and the use of a probabilistic approach to quantify uncertainty in such situations has not previously been attempted. A significant contribution of the current project is therefore to develop a methodology for incorporating climate model uncertainty into the simulation tools. This represents an amendment to the original project plan, which was agreed with the DEFRA project officer in April 2005.

A further complication is that precipitation estimates for climate models have historically been poor. As a result, existing downscaling methods generally use climate model outputs other than rainfall (Wilby et al., 1998). This project takes a similar approach, although we have also investigated the ability of RCMs to reproduce various properties of observed rainfall data.

The project has focused mostly on the generation of rainfall sequences at a single spatial location. This is often adequate for the hydrological modelling of small homogeneous catchments; however, there is a need for a spatial representation of rainfall to ensure realistic streamflow generation when catchment size or heterogeneity is sufficiently large (Wheater, 2002). To address this need, we show how a multi-site rainfall generation algorithm from project FD2105 can be used in conjunction with the single-site methodology developed here, to simulate spatial rainfall sequences incorporating scenarios of climate change.

On the basis of these considerations there were three main tasks for this project. These corresponded to individual work packages. A fourth work package aimed to demonstrate the functionality of the proposed methodology by implementing it in full for the single-site case. In summary, following the amendment to the project plan in April 2005 (see above), the project work packages were as follows:

Work Package 1: To evaluate the most recent climate model outputs. This was split into three subtasks:

- *Work Package 1.1: Review of climate models* – to provide a summary of methods that have been used so far to incorporate climate model outputs into hydrological applications, and to identify specific models that are potentially suitable for use in a UK rainfall simulation exercise.
- *Work Package 1.2: Verification of selected model outputs* – to determine the extent to which climate model outputs capture the structure of rainfall sequences, identify the variables that are of most use in driving rainfall simulations, and build a set of daily rainfall models incorporating climate model outputs.
- *Work Package 1.3: GCM uncertainty* – to investigate the results when the daily rainfall models from WP1.2 are conditioned on the output from different GCMs under future climate scenarios.

Work Package 2: To develop and validate downscaling methods for the generation of single-site rainfall:

- *Work Package 2.1: Single-site cluster model calibration with Generalized Linear Models* – to combine the daily rainfall models from WP1.2 with hourly properties that are invariant across a wide variety of atmospheric conditions, so as to enable the calibration of nonstationary single-site models for subdaily rainfall.
- *Work Package 2.2: Provision of simulation methodology incorporating climate model uncertainty*.

Work Package 3: To develop and validate downscaling methods for the generation of multi-site rainfall.

Work Package 4: To demonstrate the functionality of the methods, by implementing the full rainfall simulation methodology for the single-site case. As part of this work package, supporting material and documentation has been made available on the project web site (see below).

The scientific objectives of the project have been achieved in full. With the agreement of the project steering committee, the methodology for generating future rainfall sequences has been illustrated in all cases using the SRES 'A2' greenhouse gas emissions scenario, in which total annual CO_2 emissions in 2100 are approximately 3.5 times greater than in 2000 (IPCC, 2001, Appendix II SRES Tables).

In the remainder of this report, Section 2 gives a brief review of climate models and existing downscaling methodologies (WP 1.1), and summarises the overall approach taken here. Sections 3 and 4 describe the work on single-site rainfall generation for daily and subdaily data respectively (WP 1.2, 1.3 and 2.1), and Section 5 considers the multi-site case (WP 3). Climate model uncertainty (WP 2.2) is dealt with in Section 6, and a summary of overall functionality (WP 4) is provided in Section 7. Conclusions and recommendations are given in Section 8. Figures are provided in an Appendix. All of the work is described in detail in a series of project reports, listed in Table 1. These reports are provided as supporting material with the present summary. They are also available, along with software and other useful resources, from the project web site: http://www.ucl.ac.uk/Stats/research/Rainfall/index.html. Throughout the text below, they are referenced by number e.g. "Report 2".

Table 1 Summary of detailed technical reports produced during the project

Report Number	Title	Author	Date	WP
1	*Review of methods for deriving local scale precipitation from future climate model scenarios*	N. Leith	Jan 2005	1.1
2	*The use of generalized linear models to simulate daily rainfall under scenarios of climate change*	N. Leith	Dec 2005	1.2, 1.3
3	*Point process models for subdaily rainfall simulation*	N. Leith	Sep 2006	2.1
4	*Multi-site downscaling for the Blackwater catchment*,	A.J. Frost, R.E. Chandler, M.-L. Segond	Sep 2006	3
5	*Climate model uncertainty*	N. Leith	Dec 2006	2.2
6	*Demonstration of integrated methodology*	R.E. Chandler, N. Leith	Mar 2007	4
Technical note #1	*Summary of BSc dissertation "Representation of rainfall by regional climate models" by Birgit Schrödle*	R.E. Chandler	Oct 2005	1.2

2. Overview of the project

2.1 Approaches to downscaling

The first task for this project was to establish the approaches to downscaling that have been taken in the past, with particular emphasis on the provision of precipitation scenarios for hydrological applications. Report 1 is a review of the literature in this area. The important features to emerge are as follows:

1. Downscaling methodologies can be classified as either *statistical* or *dynamical*. Dynamical methods are physically based and involve the use of RCMs, as described above. Statistical methods, on the other hand, exploit relationships between precipitation in some relevant spatial area and time interval (e.g. daily precipitation at a certain rain gauge) and large scale features of the surrounding atmosphere.
2. Both statistical and dynamical methods need to be used with care. The main concerns with RCMs are: firstly, that it is difficult to generate a large number of possible rainfall sequences due to computational costs; secondly, that even the enhanced spatial resolution of an RCM is typically too coarse for direct input into hydrological process models; and finally, there are questions regarding the ability of RCMs to generate realistic precipitation sequences. To investigate this latter issue, as part of this project a comparison was carried out between RCM and observed

rainfall data for a lowland area in south-east England and an upland area in north-east Lancashire respectively. The results (summarized in Technical Note No. 1 – see Table 1) showed that many properties of RCM precipitation are in reasonable agreement with observations, if an ensemble of RCMs is used. However, several discrepancies were also highlighted: no single RCM accurately reproduced all the properties considered, and no one model could be considered as 'best'. These conclusions agree with others in the literature (see, e.g., Frei *et al*. 2003).

3. The use of statistical downscaling methods is itself dependent on certain key assumptions as set out by, among others, Wilby *et al*. (1998a); Wilby and Wigley (2000) and Charles *et al*. (2004). These assumptions are: firstly, that local scale rainfall responds at least in part to changes in large scale atmospheric structure; secondly, that the relevant aspects of large scale structure, and its change in response to greenhouse gas forcing, are realistically represented by the climate models at the scales used for analysis; and finally that the observed relationship between local precipitation and large scale structure remains valid under altered climatic conditions. Throughout the present project, care has been taken to ensure that these assumptions are at least plausible. Apart from this, a drawback of current statistical methods is that they do not explicitly allow for the representation of feedback mechanisms in the generated scenarios because, by definition, the climate model outputs are generated before the precipitation sequences (Wilby *et al*, 2004). The significance of this for flood risk assessment in the UK is not known at present.

4. Statistical methods for downscaling to a daily timescale can be broadly categorized as follows:

   a) *Transfer functions*. These attempt to derive relationships between rainfall and large-scale atmospheric variables. The output is essentially an estimate of the expected rainfall for a given large-scale atmospheric configuration. It is generally accepted that transfer function methods do not predict the magnitude of extreme rainfall events well. This is unsurprising, since they merely estimate the expected rainfall and hence are guaranteed to under-represent variability.

   b) *Weather typing*. Here, an attempt is made to classify the large scale atmospheric structure as belonging to a certain 'weather type' and to associate either a rainfall mean or a complete rainfall distribution with each of these types. During this project, attempts were made to replicate this kind of analysis using different datasets, but with limited success.

   c) *Weather generators* are models that can be used to simulate whole sequences of daily rainfall data, explicitly representing both the dependence of rainfall upon atmospheric structure and its persistence over successive days. Dependence upon atmospheric structure is usually incorporated by linking the parameters of a stochastic rainfall model to the values of atmospheric variables. There are many ways of constructing weather generators; Report 1 gives details. Although the possibility of representing complete rainfall sequences is intuitively appealing, many weather generators in current use are unable to reproduce all of the features relevant in hydrological problems. A common deficiency is under-representation of variability at monthly and longer time scales (Wilks and Wilby 1999), which could affect moisture budget calculations in hydrological models.

5. Statistical methods for downscaling to a subdaily timescale are much less well developed. In the UK, the main contributions are those of Kilsby *et al*. (1998), Fowler *et al*. (2000) and Fowler *et al.* (2005). In each case, the idea is to link the parameters of a subdaily rainfall model to large-scale atmospheric conditions, either by relating these parameters to statistical properties of subdaily rainfall and investigating how these statistical properties are likely to change in an altered climate or by using separate rainfall model parameterizations for different weather states. The work of Fowler *et al.* (2005) provides the ability to generate subdaily sequences at multiple sites.

In this project, the basic approach is to use a weather generator for daily rainfall, and to use similar ideas to those in Kilsby *et al. (1998)* for subdaily rainfall. The generator used here was developed in project FD2105 and improves upon many existing generators in many respects; for example, interannual variability is well represented as shown below. For subdaily generation, we relax some of the assumptions in Kilsby *et al*. (1998) about future changes in subdaily rainfall model parameters. Instead, we rely on empirical scaling relationships between rainfall properties at different time scales. It has been demonstrated that these relationships are remarkably stable across the UK and at different times of year. This gives some confidence that they hold under a wide variety of atmospheric conditions, and hence that they should remain valid in a moderately changed climate.

2.2 Review of methodology developed in FD2105

The methods developed here extend those developed in project FD2105. To provide some context therefore, we here summarise the basic tools as developed there.

2.2.1 Generalised linear models for daily rainfall

At the heart of the work reported here is the use of Generalised Linear Models (GLMs) for daily rainfall. These are designed both to take advantage of the relative abundance of long sequences of daily raingauge data, and to represent spatial and temporal nonstationarities in rainfall sequences. A GLM can be regarded as an extension of the classical linear regression model, in which a probability distribution is linked to the values of spatially and temporally varying predictors. In fact, for rainfall modelling this distribution is specified in two parts: the probability of rainfall occurrence is modelled separately from the amount of rain if non-zero. The methodology, which is well established in the statistical literature, was first applied to daily rainfall by Coe and Stern (1982), who focused on single-site analyses. Chandler and Wheater (2002) extended their work, proposing a GLM-based framework for interpreting spatial-temporal structure and applying this framework to the analysis of daily rainfall sequences in the west of Ireland. In work carried out as part of FD2105, Yang *et al.* (2005) showed that GLMs were capable of generating nonstationary multi-site rainfall sequences reproducing many properties of observed rainfall, including extremes, over a range of spatial scales. Typically, predictors in a GLM for rainfall will include previous days' rainfalls (to account for autocorrelation), together with quantities representing regional variation (such as site altitude) and seasonal variability. The present project has also explored the use of atmospheric variables at large space and time scales as predictors. The effect is that each day's rainfall at each site is regarded as drawn from a different distribution. By conditioning on atmospheric variables, the GLMs are able to represent the way in which local rainfall distributions respond to large-scale atmospheric conditions. Models can be specified in such a way that the effect of one predictor depends on the values of others; this is important to obtain a realistic representation of the processes involved. For example, our results show (as seems intuitively reasonable) that warmer temperatures are associated with more frequent rainfall in winter, but that the reverse is true in summer.

To use a GLM, it is necessary first to choose appropriate predictors and to estimate the model parameters that are appropriate for the catchment of interest. This is achieved by fitting the model to daily rainfall data from one or more gauges in the area. After fitting the model, many simulations can be generated very cheaply. Both model fitting and simulation can be carried out using the GLIMCLIM software package (Chandler, 2002), which can be obtained via the project web site.

2.2.2 Poisson cluster models for subdaily rainfall

GLMs provide a powerful means of generating realistic daily rainfall sequences at single or multiple sites. However, they are not suitable for use at subdaily time scales, because an excessive number of parameters would be required to describe adequately the complicated structure of rainfall at such scales. Instead therefore, the FD2105 methodology uses models based on Poisson cluster processes to generate subdaily rainfall sequences (see Onof *et al*. 2000 for a review). This type of model has been used for over 25 years for stochastic rainfall generation. The idea is to represent the rainfall process as a collection of storms. Each storm consists of a cluster of rain cells which, in the single-site case, each have a random lifetime during which they deposit rain at a constant rate. The total rainfall at time t is the sum of contributions from all cells active at time t. The models are parameterised in terms of physically interpretable quantities such as storm arrival rate, mean intensity and duration of a rain cell and mean number of cells per storm. There are many such models in current use; the most popular are based on the Bartlett-Lewis and Neyman-Scott clustering mechanisms. In FD2105, the recommended model for national application in the UK was the random-parameter Bartlett-Lewis model of Rodriguez-Iturbe *et al*. (1988). In practice, however, there is very little to choose between the two mechanisms in terms of performance, and a Neyman-Scott model is equally well justified.

To use a Poisson cluster model, it is necessary first to estimate the parameters. This is usually done so as to achieve as close a possible a match, according to a weighted least-squares criterion, between the observed and modelled values of selected properties ('fitting statistics'). In FD2105, an investigation was conducted to determine the most appropriate fitting statistics for use in the UK. The recommended statistics were: mean hourly rainfall; variances of 1-, 6- and 24-hourly rainfall; proportions of dry hours and days; and lag 1 autocorrelations for hourly and daily rainfall. In the least-squares criterion, these statistics are weighted so as to contribute approximately equally to the objective function. To obtain a reliable minimisation of the least-squares criterion is often computationally challenging. Software for fitting and simulating these models, written in the R environment (R Development Core Team, 2006) is available from the investigators on request.

Although the Poisson cluster models have interpretable parameters and are able to reproduce many properties of observed rainfall sequences, they have some drawbacks. For example, their reproduction of rainfall extremes can be variable (Wheater *et al*., 2006). Also, they typically require hourly records of at least 15 years' duration in order to obtain fitting statistics that are accurate enough to estimate the model parameters reliably; such data may not always be available. Finally, the models are stationary: the only way to generate nonstationary sequences is by allowing the parameters to vary through time. In the literature, typically a separate set of parameters has been used for each month of the year; this accounts for seasonality but not interannual variability or climate change. Kilsby *et al*. (1998) suggested that climate change could be accounted for in a Neyman-Scott model by selecting two of the model parameters and allowing these to vary in line with projected changes in mean rainfall and the proportion of dry days. The approach taken in the present project is similar to this, except that changes in all of the fitting statistics are considered and all model parameters are allowed to change through time. An alternative approach is that of Fowler *et al*. (2000, 2005), who associated the model parameters with different weather types; by implication, climate change scenarios can be accommodated in response to changes in the frequencies of these different types. This latter approach has not been adopted here, due to difficulties in reproducing results from weather typing techniques (see Section 2.1).

2.2.3 Multi-site disaggregation

The GLMs of Section 2.2.1 can be used to generate nonstationary single- or multi-site sequences of daily rainfall, whereas the Poisson cluster models of Section 2.2.2 can be used to generate single-site hourly sequences. There are a number of more or less complex ways in which multi-site subdaily sequences could be obtained. In FD2105, a simple method was advocated for use in the short term. The idea is to combine a multi-site GLM with a single-site Poisson cluster model at one gauge (the 'master gauge'), using the disaggregation procedure of Koutsoyiannis and Onof (2001); for each day, the resulting hourly temporal profile at the master gauge is then applied to all other gauges as well. Despite its simplicity, this approach was shown to perform reasonably in many respects. Its main shortcoming is a tendency to overestimate the variability of areally averaged rainfall.

In the present project, we demonstrate how this simple multi-site disaggregation procedure can be used in conjunction with GLM simulations that incorporate climate change scenarios.

2.3 Summary of the procedure

The primary aim of this project is to develop a methodology for generating synthetic daily or subdaily rainfall sequences at a given location, conditioned on the outputs of numerical climate models for some future time period. This is a complex task. In the single-site case, the main steps are as follows:

1) Assemble an appropriate archive of data for the location of interest. The minimum requirement is:
   a) A single quality-controlled daily rainfall record, of at least 20 years' duration and with at most 10% of daily values missing.
   b) Spatially averaged monthly values of temperature, sea level pressure and relative humidity, for the same period as the rainfall record.
   c) The corresponding spatially averaged values for the future time period of interest, from one or more climate models.

   For multi-site simulation, multiple daily rainfall records are required. The precise number depends on catchment size and heterogeneity; the main consideration is that enough data are available to capture the main systematic features of rainfall variation over the catchment. Subdaily rainfall records may be used if available; however, the methodology does not require them.

2) Fit models to the data assembled in step (1), as follows:
   a) GLMs for rainfall occurrence and amounts should be fitted to the daily rainfall record(s) from step 1a), using the atmospheric variables from step 1b) as predictors. This fitting can be carried out using the GLIMCLIM software package; template model definition files for single-site modelling are available from the project web site.
   b) If using the pilot methodology, described in Section 6 below, for handling climate model uncertainty, fit a Bayesian hierarchical time series model to the climate model data from step 1c).

3) Use GLIMCLIM to simulate the fitted GLMs a large number of times over the future period, with spatially averaged climate model outputs as predictors. The precise details of this step depend on the approach adopted for handling climate model uncertainty. The options are as follows:
   a) Condition all of the simulations on a single realisation from a single climate model. This ignores climate model uncertainty altogether, and is not recommended.
   b) Perform separate sets of simulations conditioned on single realisations from several climate models, and then merge the results. This is a relatively crude means of handling climate model uncertainty, but it has the advantage of simplicity and is preferable to (a). Furthermore, it enables climate models to be 'weighted' to reflect beliefs about their relative reliabilities in any particular setting.
   c) If using the pilot methodology described in Section 6 below, perform separate sets of simulations, each conditioned on a single realisation from the posterior distribution of the future atmospheric variable sequence. This approach provides the most coherent way of incorporating climate model uncertainty into future scenarios, but is computationally demanding.

4) If subdaily data are required then, for each climate model realisation in step 3:

   a) Calculate selected statistical properties of the daily GLM simulations for each month of the simulation period, and use the method described in Section 4 below to reconstruct the corresponding properties of subdaily rainfall.
   b) Fit a Poisson cluster model separately to each month of the simulation period, using the simulated and reconstructed properties as fitting statistics.
   c) Simulate as many realizations as required from the sequence of fitted Poisson cluster models.

For multi-site simulation, steps (1) to (3) are unchanged. However, step (4) is replaced by the multi-site disaggregation procedure described in Section 5 below.

At present, the implementation of the entire procedure outlined above is quite computer intensive and requires a lot of manual intervention. The core of the process – the fitting and simulation of GLMs – can be achieved straightforwardly, however. Where appropriate, computer code for the various tasks is available from the project web site (see Section 1).

2.4 Data sources

As indicated in the previous subsection, various different types of data are required to implement the methodology developed in this project. Here we summarise the data that have been used in developing and testing the methodology.

2.4.1 Rainfall data

The first requirement for the methodology is a set of historical rainfall data (Section 2.3, step 1a). The primary source of rainfall data for the project is a set of three hourly records from Heathrow, Birmingham (Elmdon) and Manchester (Ringway) airports. These data have been aggregated to a daily time scale where necessary. Data from the 1961-1990 period have been used throughout, for compatibility with the other data sources described below. This will be referred to subsequently as the 'control period'. Data are missing at Heathrow for January to August of 1988 and February 1989, and at Elmdon for December 1983 and August 1989. The record for Ringway is complete.

For the investigation of subdaily rainfall structure in Work Package 2 (see Section 4), the three hourly records above have been supplemented by quality-controlled records from nine other locations in England and Wales, provided by the Environment Agency. Most of these are in upland areas, to complement the relatively low-lying airport data. The record lengths vary from 7 to 20 years.

The multisite downscaling methodology for Work Package 3 (see Section 5) is illustrated using daily data from a network of 34 gauges run by the UK Meteorological Office. The gauges are in the 50km × 40km catchment of the River Blackwater in Surrey. The data run from 1961 to 2000, and were also used in FD2105. Further details are given in Wheater et al. (2006, Chapter 9) and in Yang et al. (2005).

2.4.2 Atmospheric variables

In addition to rainfall data, the methodology requires historical values of spatially averaged atmospheric variables (Section 2.3, step 1b). Two sources of atmospheric data have been used in the project: these are the NCEP (Kalnay et al., 1996) and ERA40 (at http://data.ecmwf.int/data/d/era40/) reanalysis data sets, in which gridded values of many different variables have been derived by feeding quality controlled observations into a physical model. Data are available at a daily time scale, although for the most part we have considered monthly aggregates. Again, the 1961-90 control period is considered. Most of the work uses the NCEP data, which are taken from the archive supplied with the Statistical DownScaling Model (SDSM; Wilby and Dawson, 2004). In this archive the data are on a grid of 2.5° latitude by 3.75° longitude, with nine grid squares covering the UK; however, the values for three of these are obtained by averaging over their neighbours (see Wilby and Dawson, 2004, Figure 2.2). These three have not been used in any of the subsequent analysis, since they merely duplicate information from the remaining six.

In any reanalysis data set, some variables (e.g. temperature) are more closely related to the input observations than others (e.g. precipitation), and hence are more reliable. In this project, only the most reliable variables (classified as 'category A' in the NCEP dataset) have been considered.

2.4.3 Climate model data

Finally, the methodology requires spatially averaged atmospheric variable data for the future, derived from climate models (Section 2.3, step 1c). Data from both GCMs and RCMs have been used here. The future period considered is 2071-2100, and for this period all results are based on the SRES A2 greenhouse gas emissions scenario (see Section 1).

The RCM data were obtained from the PRUDENCE (Prediction of Regional scenarios and Uncertainties for Defining EuropeaN Climate change risks and Effects) project (http://www.prudence.dmi.dk). This project produced high-resolution (grid distances of between 0.2° and 0.5°) climate simulations, using RCMs from several European climatological institutions. Three different RCMs have been considered, on the advice of the project steering committee. These are from the Danish Meteorological Institute (DMI), the UK Hadley centre (HC) and the Swedish Meteorological and Hydrological Institute (SMHI). The DMI and SMHI models were forced using a different GCM to that from the Hadley Centre.

As noted in Section 1, different climate models can give very different projections for future climate. It is becoming clear (e.g. Rowell 2004, Wilby and Harris 2006) that, when using RCMs to construct future climate scenarios, the uncertainty due to RCM formulation is relatively small compared with that resulting from the formulation of the driving GCM. Therefore, to investigate GCM uncertainty, we also consider output from four different GCMs, developed respectively by the Canadian Centre for Climate Modelling and Analysis (CCCma; model CGCM2), the Commonwealth Scientific and Industrial Research Organisation (CSIRO; model CSIROMK2), the Max-Planck-Institute

(MPI; model ECHAM4) and the Hadley Centre (HC; model HADCM3). The GCM data were obtained from the SDSM archive, and are provided on the same grid as the NCEP data described above.

As well as using data from the future period (2071-2100), control period output from all of the climate models has been used. This enables us to compare the properties of rainfall sequences driven respectively by climate models and by actual atmospheric data for the same period. In turn, this provides a context within which to interpret any differences between control and future period simulations.

3. Daily rainfall generation at a site

In this section we summarise progress and discuss results for single-site daily rainfall generation. Report 2 gives further details of the work reported here. The main achievements are as follows:

1. An appropriate set of atmospheric variables has been identified for use in climate change rainfall simulations. These are temperature, sea level pressure and near surface relative humidity. Temperature and sea level pressure are generally well represented in climate models. Although some models perform less well with respect to humidity measures (Harris, 2004), our results indicate that the inclusion of humidity in the rainfall models is beneficial in terms of their overall performance.

   In the models constructed here, spatially averaged atmospheric variables, standardised with respect to monthly control period means and standard deviations, are used as predictors in the rainfall models. The spatial averages are defined as weighted averages of the gridded atmospheric data. Let d be the distance (in kilometres) between the centre of a grid square and the site of interest; then, when calculating the weighted average, the weight associated with that grid square is proportional to $\max(0, 360 - d)$. This ensures that the spatial extent of the averaging is approximately equivalent to a single grid square. The monthly standardisation is performed after the calculating the spatial averages.

2. It has been established (see Report 4) that realistic rainfall simulations can be obtained using monthly, rather than daily, time series of atmospheric variables as predictors in the GLMs. This is useful because climate model years have 360 days only (30 days per month) but the GLIMCLIM software uses calendar dates; this creates a mismatch if simulations are required based on daily climate model data. There are small differences between the properties of GLM simulations driven by daily and monthly atmospheric predictors, but these are minor compared with the overall variability in these properties.
3. It has been established that at different sites, the basic structure of GLMs for daily rainfall is similar (i.e. similar predictors are required), although the model parameters vary between locations. We are therefore able to provide template GLIMCLIM model definition files for general use. To obtain models for use at a new location, it is necessary merely to run the GLM fitting programs in conjunction with these templates. For rainfall occurrence, the required predictors include all three

atmospheric variables along with seasonality and rainfall up to three days previously. The effects of temperature and relative humidity are both seasonally varying, as is the dependence upon previous days' rainfall. The predictors for wet day rainfall amounts are similar, except that relative humidity is no longer important and it is sea level pressure, rather than temperature, that has a seasonally varying effect.

4. It has been established that model calibration and performance is insensitive to differences between the NCEP and ERA40 reanalysis data sets.
5. It has been established that for the control period, properties of GLM simulations conditioned on standardised climate model output are indistinguishable from those of simulations conditioned on the reanalysis data sets. This is important, because it means that regardless of the atmospheric sequences used in the control period, any differences between the properties of control and future rainfall simulations can reasonably be ascribed to changes over time, rather than to intrinsic differences between simulations driven by observations and by climate models.

The fitted models are able to reproduce a wide range of daily rainfall properties for the control period. To illustrate this, Figure 1 shows some results obtained from 200 GLM simulations for the 1961-90 period at Elmdon, conditioned on NCEP reanalysis data for this period. For each simulation, several summary statistics have been computed for each month of the year. The net result is a set of simulated distributions for each summary statistic. If the model is reasonable, the observed values of these statistics should look like samples from the simulated distributions. The bands in each panel of the figure show the percentiles of the simulated distributions, with the observed values shown in black. There is generally good agreement, particularly for the mean and proportion of wet days. There is, however, a tendency for the simulated standard deviations to be slightly too small during summer months. This is associated with the use of gamma distributions with a constant shape parameter (but varying means) to model rainfall amounts, and may lead to slight underestimation of summer rainfall extremes in GLM simulations of daily rainfall (as has been shown by Yang *et al*., 2005).

To demonstrate the capability of the GLMs to represent interannual variability, and to illustrate their response to climate change scenarios, Figure 2 shows simulated distributions of seasonal rainfall at Heathrow, for both control and future periods. The left-hand panels show a clear relationship between observed totals and simulated distributions during the control period, and also that the simulated distributions have realistic levels of variability (a more detailed assessment of this may be found in Report 2). The width of the black band increases in 1989; this reflects uncertainty due to missing observations, which is handled by the GLMs (see Yang *et al*., 2005). For the future period, the summer distributions are shifted down slightly but the winter distributions are shifted up. This suggests a tendency for drier summers and wetter winters under this greenhouse gas emissions scenario. This is in agreement with other projections for the south-east of England (e.g. Hulme *et al*., 2002) and, qualitatively, with the changes in precipitation simulated directly by the GCM. However, the overlap between control period and future probability distributions make it clear that not every summer will be drier, and not every winter will be wetter. The extent of this overlap is a consequence of the fact that the atmospheric variables explain only a small amount (typically less than 10%) of the variance in observed daily rainfall sequences; most of the variability in the simulated rainfall is therefore attributable to the stochastic component of the models, rather than to the information in the GCM.

Another feature to emerge from Figure 2 is that the simulated distributions vary substantially from year to year, in both control and future periods. This is because they track the underlying atmospheric variable sequence. Clearly, for the future period this is just one of many possible sequences; the peaks and troughs in the generated rainfall distributions would occur in different years if forced using another run of the same GCM with slightly different initial conditions, although the overall properties would be similar. Thus, even within a single GCM, the use of a single realization will underestimate the variability in rainfall sequences in any given year. Moreover, if different climate models are used, the differences are accentuated. This is shown in Figure 3, in which the first seven panels show simulated distributions of annual rainfall driven by atmospheric variables from each of the different climate models considered in this project. For example, the trends from the CCCma and Hadley Centre GCMs (first and last plots in the top row of the figure) are in opposite directions. The final panel in the figure is obtained by merging the simulated realizations from all of the climate models. This represents a crude way of dealing with climate model uncertainty (see Section 2.3); the overall distributions here clearly bear little resemblance to those obtained from any individual climate model.

4. Subdaily rainfall generation at a site

In this section we summarise progress on the development of methods for generating subdaily rainfall sequences under an altered climate. As described in Section 2.2.2, this is achieved by allowing the parameters of a Poisson cluster model to vary through time. At any time point, the parameters are derived from statistical properties of both daily and subdaily rainfall at that time point. In most applications of these models, rainfall records are assumed to be stationary in time and the required statistical properties are estimated by pooling data from each year of the observed record. However, the GLM simulations of the previous section provide an alternative way to estimate summary statistics at an individual time point, at least for daily rainfall. This is because the GLMs can be simulated many times to provide a large number of replications of the rainfall process; the required fitting statistics (such as the mean, variance and probability that a day is wet) can then be calculated at any time point from these replications.

The basis of our work on subdaily rainfall is the existence of stable relationships between rainfall properties, notably the variance and proportion of wet intervals, at different time scales. This is illustrated in Figure 4. Here, summary statistics for different levels of temporal aggregation have been calculated separately for every month of the observed rainfall record at Heathrow and Malham, the two most contrasting sites in our subdaily rainfall database. The plots show the dependence between the logarithm of the summary statistic and log time scale. Only results for January and July are shown; each line represents data from a single year at an individual site. The first striking feature of the plots is that the relationship between log timescale and log statistic is very close to linear in almost all cases. This seems to be a general feature of rainfall in many parts of the world and has been noted previously by, among many others, de Lima and Grasman (1999); Güntner et al. (2001) and Smithers et al. (2002). What is perhaps more remarkable is the similarity between the slopes of the lines, particularly for the variance. The plots here are typical of those obtained from all of the sites for which we have data. This similarity between the slopes suggests that once the variance, or proportion of wet intervals, is known for daily rainfall, then this can be extrapolated back to obtain a reliable estimate of the corresponding property at any time scale down to hourly. It also suggests that similar scaling relationships hold under a wide variety of different conditions – in winter and in summer, at different locations in the UK – and hence that they may be expected to hold in a moderately altered climate as well.

In the light of these results, the main achievements of the project with respect to single-site subdaily rainfall generation are as follows (see Report 3 for further details):

1. The linear scaling relationships suggested by Figure 4 have been explored in detail. Theoretical considerations indicate that, for the variance at least, the relationships cannot be exactly linear, since this would lead to the same lag 1 autocorrelation at all time scales (which is known to be unrealistic). Further, the slopes cannot be exactly the same for each month and site, since this would lead to the same lag 1 autocorrelation throughout the year and in all locations.
2. To overcome the difficulties noted in (1), models have been fitted in which the lines in Figure 4 are represented as quadratic functions of log(timescale), and in which the slopes are allowed to depend on the large-scale atmospheric predictors used in the daily rainfall GLMs. The autocorrelations implied by the resulting variance models show excellent agreement with observations, with respect to seasonality. Initially, the analysis was based only on data from the three airport sites, and the resulting models were tested by trying to reconstruct subdaily rainfall properties from the corresponding daily ones at other sites. The performance was generally good at lowland sites, indicating that the fitted scaling relationships are widely applicable. However, discrepancies were observed at upland sites in the north and west of the UK.
3. We have investigated the discrepancies noted in (2) regarding upland sites, and concluded that they can probably be resolved by allowing the slopes of the scaling relationships to depend on site altitude as well as the atmospheric predictors. However, further work using data from a more extensive network of subdaily raingauges is needed to confirm this. If valid, this conjecture would still provide the required set of relationships that hold under a wide range of conditions.
4. For the control period, the fitted scaling relationships have been used to reconstruct subdaily rainfall properties from the daily properties derived from GLM simulations; these reconstructed properties have then been used to fit random parameter Bartlett-Lewis models (see Section 2.2.2). Separate exercises have been carried out: in the first, a single set of Bartlett-Lewis model parameters has been derived for each month of the year (this is referred to as “Strategy 2” in Report 3) and in the second a separate set of parameters has been derived for each month of each year (“Strategy 3”). Strategy 3 is much more computationally demanding, but is arguably

more realistic since it allows the Bartlett-Lewis model parameters to respond more directly to the large-scale atmospheric inputs. The resulting estimates have been compared with those obtained from the methodology developed in FD2105 ("Strategy 1"), where parameters are estimated from properties computed directly from an observed rainfall record. Specimen results are shown in Figure 5, for Ringway. Here, strategies 1 and 2 have been used to derive the solid and broken lines respectively. Notice that the seasonal variation in parameters is much smoother using strategy 2, because the GLM simulations enable the daily, and hence subdaily, properties to be estimated much more precisely. This relies, of course, on the assumption that the GLM simulations are realistic, but this has already been demonstrated. The precise interpretation of all model parameters is given in Report 3; here, we note merely that the first two plots in Figure 5 relate to the parameters λ (storm arrival rate, in hr^{-1}) and μ_X (mean cell intensity, in mm hr^{-1}). The seasonal cycles in both parameters are realistic: storms occur less frequently in summer than in winter, but have more intense rain cells.

5. A similar exercise to (4) has been carried out, to estimate parameters in the Bartlett-Lewis model for the future period. Parameters have been estimated using reconstructed rainfall properties derived from GLM simulations conditioned on output from all seven of the climate models considered. Figure 6 compares selected parameter estimates for the control and future periods, the latter being derived from simulations conditioned on the Hadley Centre GCM. The results again relate to Ringway, but here the parameter estimates are both derived using strategy 3. Since both control and future periods are of 30 years' duration, this strategy in fact delivers 30 parameter sets for each month of the year; the values plotted in Figure 6 are the medians of each set of 30 estimates. The future estimates of λ, the storm arrival rate, show an enhanced seasonal cycle relative the control period, with fewer storms in summer and more in winter. The figure also suggests an increase in both mean cell intensity and duration throughout most of the year, along with a reduction in the mean number of cells per storm. These results are qualitatively similar to those obtained using the other climate models, and are of interest in that they provide an interpretation for the mechanisms underlying the future changes.
6. The properties of subdaily rainfall simulations have been investigated via simulation. For the control period, a 30-year simulation was run for each of the strategies discussed in (4) above. For the future period a 30-year simulation was run for the Strategy 3 parameter sets corresponding to each of the climate models. These simulations showed that the fitted models were able to reproduce the scaling relationships upon which the subdaily methodology is based. For the control period, there was generally a good match between observed and simulated rainfall properties, except that strategy 3 led to slightly better reproduction of the proportion of wet intervals. The main deficiencies were a slight underestimation of rainfall variance in summer, which can be traced back to the GLMs (see Section 3), and an associated tendency to underestimate hourly rainfall extremes.

   For the future period, the simulation results suggested that mean hourly rainfall, proportion of wet hours and hourly rainfall variance will increase in winter and decrease in summer at all three sites examined. The strength of these tendencies varied with the underlying climate model. For extreme events, return periods are projected to decrease. For example, depending on the climate model used, a 50-year event in the control period has a return period of approximately 3 to 15 years in the future.

Overall, significant progress has been made in the generation of nonstationary rainfall sequences at a subdaily time scale. As well as providing a methodology for subdaily rainfall simulation, the projected changes in Bartlett-Lewis model parameters provide an insight into possible future changes in the mechanisms of the rainfall process. A final contribution is that by making minimal assumptions about the precise nature of changes in rainfall properties or model parameters, the work here provides a means of assessing the validity of assumptions made in other approaches. For example, Kilsby *et al*. (1998) suggested allowing just the storm arrival rate and mean cell intensity to change in the future. Our results confirm that these parameters show clearly defined and systematic changes in the future, but also demonstrate that other parameters may be expected to change as well.

At present, the main deficiency in the subdaily simulation methodology developed here is the under-representation of variability in summer, with an associated underestimation of hourly extremes. This seems to be associated largely with the daily rainfall properties simulated by the GLMs; the small discrepancies in daily rainfall properties are magnified at a subdaily time scale. It is therefore likely that the problems could be resolved by relaxing the assumption of a constant shape parameter in the GLMs for daily rainfall amounts.

5. Multi-site rainfall generation

In Work Package 3 of the project, the single-site methodology from Work Packages 1 and 2 has been combined with the spatial-temporal modelling techniques from project FD2105, to produce a tool for generating multi-site sequences of subdaily rainfall incorporating scenarios of climate change.

Although several methods have been proposed in the literature for the generation of multi-site rainfall sequences at a daily timescale (see Section 1 of Report 4 for references), there is much less available on the generation of subdaily sequences. Indeed, apart from the methodology of Segond et al. (2006) used here, the only work we are aware of that allows the possibility of incorporating temporal nonstationarity into multi-site subdaily sequences is that of Fowler et al. (2005) (see Section 2.1). The work reported here therefore represents a major step forward. The methodology is described more fully in Wheater et al. (2006) and Segond et al. (2006). Hourly sequences are derived by combining the daily output from a GLM with the HYETOS single-site disaggregation process (Koutsoyiannis and Onof, 2000, 2001), which is based on Bartlett-Lewis models. This single-site generator produces hourly totals that are consistent with the daily amounts at one of the sites of interest. The resulting sub-daily temporal pattern is then applied uniformly in space to obtain subdaily sequences of rainfall at multiple sites.

The main steps in the proposed procedure are:

1. Fit a GLM simultaneously to daily rainfall data from several sites in the catchment of interest, using large-scale atmospheric variables as predictors as in the single-site case.
2. Use the GLM to generate multi-site daily rainfall series over the time period of interest.
3. Taking a cluster of wet days, defined as a series of consecutive wet days delimited by at least one dry day, use the HYETOS model to simulate hourly rainfall at one raingauge (the ‘master gauge’), and disaggregate using an adjusting procedure so that the hourly totals sum up to the daily totals.
4. Use the hourly pattern generated at the master gauge to disaggregate the daily information to hourly rainfall at the other gauges.
5. When the master gauge records zero rainfall, an arbitrary profile of hourly rainfall is required. Wheater et al. (2006) used the previous days’ temporal profile in such situations. However this can lead to the generation of unrealistically high values of hourly rainfall if, for instance, there was only one wet hour on the previous wet day so that the entire daily rainfall is allocated to a single hour. Therefore in this investigation, the previous profile is used provided no hourly rainfall depth greater than 30 mm is generated. Otherwise a uniform hourly temporal profile is applied.

Since both components of the procedure (the GLMs and the multi-site disaggregator) have been tested extensively in projects FD2105 (Wheater et al., 2006) and elsewhere in FD2113, the work reported here has been confined to an illustrative example. The data used are from the Blackwater catchment (see Section 2.4.1), and GLM simulations for the future period were conditioned on output from the Hadley Centre GCM. In general, the conclusions from this exercise were exactly as expected from the previous work; in particular, conclusions regarding future changes in multi-site rainfall properties mirror the single-site results already described. Apart from this, the main achievement from this Work Package is an improved multi-site disaggregation software package, which enables disaggregations to be carried out much more quickly than before. This offers the potential for much more extensive testing of the methodology in the future.

The methodology illustrated here is not the only way to produce multi-site nonstationary sequences using the tools developed in FD2105 and FD2113. An alternative would be as follows:

1. Simulate a nonstationary hourly series at a single site, using the methodology described in Section 4.
2. Use a multi-site GLM to generate daily sequences at all the other sites, conditional upon the daily totals at the master gauge (this can be done easily using the GLIMCLIM software package).
3. Apply the hourly temporal profile from the master gauge to the daily simulations at all the other sites.

This approach was not adopted in the current work because experience shows that the GLMs are better able to reproduce realistic levels of interannual variability than the Bartlett-Lewis type models — hence it seems better to start with a GLM simulation and to disaggregate it than to start with a simulation from a Bartlett-Lewis model. Nonetheless, it would be of interest to compare the results from the two approaches. Conversely, the HYETOS methodology provides an alternative to that described in Section 4 for generating subdaily sequences: instead of allowing the Bartlett-Lewis model parameters to evolve over time, one could simply apply HYETOS to a nonstationary single-site GLM simulation. This approach would, however, not yield any insight into the mechanisms behind changes in the rainfall properties.

6. Incorporating climate model uncertainty

The work described so far enables the generation of single- and multi-site daily and subdaily rainfall sequences, conditioned on climate model outputs. However, it has been demonstrated (see, for example, Figure 3) that the results can vary markedly depending on the climate model used. The choice of climate model thus represents a significant source of uncertainty, which must be confronted in any prudent analysis of future risk. As noted in Section 1, there has recently been a move towards probabilistic assessment of climate model uncertainty, although most of this work has focused on changes in mean climate. In the current context, since the rainfall simulations are driven by entire time series of atmospheric variables, it is necessary to consider how other properties of these series may change as well. One way to deal with this is to use a mixture of rainfall simulations conditioned on the outputs from different climate models, as in the final panel of Figure 3. A more sophisticated variant of this is to weight the different climate models according to some measure of their performance (e.g., Wilby and Harris 2006). If these weights are interpreted as probabilities, then different numbers of GLM simulations could be run for each climate model to obtain an overall distribution. This provides a simple and easily interpretable means of incorporating climate model uncertainty. However, in general it will underestimate the true uncertainty. This is because the results are constrained to lie between the limits set by the available data, but there is always a possibility that another climate model will yield more extreme projections. Therefore, in this project an alternative approach has been developed, in an attempt to overcome these limitations. Progress on this should be regarded as preliminary; the aim is to set out a coherent, interpretable and logically consistent framework within which to think about climate model uncertainty, and to demonstrate that this framework is capable of providing useful results.

The approach taken here is motivated by the observation that climate model outputs are intended to provide plausible, rather than exact, scenarios that agree with actual climate statistically rather than in detail (von Storch and Zwiers 1999, Smith 2002). If this is the case, the monthly time series from different climate models should have the same underlying structure and hence can be described using the same form of statistical model; however, the parameters of these statistical descriptors will differ between climate models. Therefore, if one can establish a distribution for the parameters that describes the 'population' of climate models, one can easily and cheaply simulate a range of future atmospheric time series. This is illustrated in Figure 7. In this schematic, data $\{Y_{it} : i = 1,\cdots,5\}$ from five "potential" GCMs are considered, although in fact only a subset (represented in black) of the GCMs are actually available. The sequences from all GCMs share common characteristics: each can be represented in crude terms as a trend with more or less regular oscillation superimposed. However, the relative magnitudes of the trends and oscillation differ between GCMs. These quantities may be regarded as statistical descriptors of the various time series, shown schematically as the values of parameters θ_1, …, θ_5 of statistical models for the series. Each statistical model itself takes the form of a probability density for the distribution of the atmospheric variable of interest at each time t, possibly conditioned on a set of predictors C_t. Finally, the θs for the different GCMs are themselves regarded as drawn from a probability distribution, represented at the bottom of the figure. This distribution represents what we think of as 'climate model uncertainty'. To generate a range of future scenarios reflecting this uncertainty, it is necessary to repeatedly sample values of θ from this distribution, each time sampling values of the atmospheric variables $\{Y_t\}$ for the given θ.

The structure just described is an example of a *hierarchical model*. Although the structure is intuitive and interpretable, model fitting is complicated. It is most easily implemented in a Bayesian framework using Markov Chain Monte Carlo methods (see, e.g., Gelman *et al*. 2003). This in turn requires the specification of prior distributions for some of the model parameters. These priors represent, in some sense, an assessment of our uncertainty regarding these parameters prior to observing the GCM data. For example, in the situation illustrated in Figure 7, a prior may need to be specified for at least the mean of the distribution shown at the bottom of the figure. In applications such as this, the results can be sensitive to the precise choice of prior (Gelman, 2006); hence it is important to choose a statistical model structure for which the parameters θ are as interpretable as possible, in order that realistic and meaningful priors can be assigned.

Against this background, the main achievements of the project in relation to climate model uncertainty are as follows (for more details, see Report 5):

1. Theoretical work has been done on the fitting of a hierarchical multivariate time series model simultaneously to data from several climate models.
2. The fitting methodology has been illustrated using monthly GCM time series data for temperature, sea level pressure and relative humidity at Heathrow. It was found that the basic time series structure from each GCM was indeed the same: for example, in the future period the temperature time series are all represented by a linear trend with a changing seasonal cycle superimposed, and a second-order autoregressive error structure. Accordingly, a hierarchical model was fitted using the WinBUGS software package (Spiegelhalter *et al*. 2004). The fitting took around 2 hours on a modern laptop with a 1.7GHz processor. The model accounts for correlations between the variables, as well as their time series structure. The required prior distributions were chosen to encompass the range of scenarios that might reasonably be entertained in the absence of any GCM data. For example, for any parameter representing the change in the underlying mean of a variable between the control period and the year 2070, a zero-mean Gaussian prior was used, with variance chosen to obtain an approximate match between the central 95% portion of

the prior and the range of observations in the control period. The interpretation is that in the absence of any GCM data, we would consider it unlikely that the mean climate in the year 2070 will lie outside the extremes of observed climate during the control period.

3. The fitted hierarchical model at Heathrow has been used to generate multiple realizations of atmospheric variable time series, for the future period; each of these realizations has been used to drive a daily rainfall simulation using the GLM discussed in Section 3, and simulated distributions of future rainfall have been examined. An example is shown in the right-hand panel of Figure 8; the distributions shown here are for the annual rainfall totals in each year from 2071-2100. For comparison, the first panel shows the corresponding distributions obtained using just the atmospheric time series from the Hadley Centre GCM and the middle panel shows the distributions obtained by pooling simulations driven by the series from all available climate models (these distributions were shown previously in the right-hand panels of Figure 3). Since all the plots are on the same scale, it is easy to see the additional uncertainty that is accounted for at each stage. In particular, the uncertainty indicated by the hierarchical model is greater than that obtained simply by pooling simulations from the available GCMs; this reflects the fact that there may be additional 'potential' GCMs that have not been used in this study and which yield more extreme projections.

The work reported here should be regarded as preliminary in nature, since the methodology has only been applied to a single example. Nonetheless, it has been demonstrated that the use of a hierarchical model is feasible with modern computing power, and that such models can be used to provide simulated atmospheric sequences for input into a daily rainfall generator. This, in turn, could in principle be used to derive subdaily rainfall sequences as described in Section 4. However, this would be computationally demanding since it would be necessary to estimate separate sets of Bartlett-Lewis model parameters for each atmospheric variable sequence. To see why this is so, consider the variance of daily rainfalls simulated by a GLM. If each GLM simulation is driven by a different atmospheric variable sequence, this variance can be partitioned into two parts: one due to differences between the driving sequences (which themselves are partly due to climate model uncertainty) and one representing 'stochastic' rainfall variability. The Bartlett-Lewis models aim to represent just this stochastic variability, which may be substantially less than that implied by the GLM simulations; hence, Bartlett-Lewis model parameters derived from such GLM simulations will not reflect the properties of any realistic individual rainfall sequence. In our view, the use of hierarchical time series models in combination with the subdaily rainfall generation methodology described in Section 4 is probably infeasible at present. In the short term, an alternative would be to disaggregate individual daily GLM simulations using a simpler approach such as the HYETOS methodology described in Section 5.

A final observation regarding the use of hierarchical models is that, as noted previously, the results can be sensitive to the choice of prior distributions. This may be seen as a disadvantage, since it forces the analyst to think carefully about how to assign priors to the various quantities that require them; furthermore, it opens up the possibility that two different analysts, with different priors, may reach different conclusions. However, the bottom line is that the methodology provides a logically consistent way of combining prior beliefs with the evidence from climate models. If two different analysts reach different conclusions using this methodology, it is not because the methodology is flawed: rather, it is because they were in fundamental disagreement at the outset, and the evidence from the climate models is not strong enough to resolve their differences. A further feature of the methodology is that it can be extended, in principle, to accommodate control period information from both climate models and observations. The incorporation of observational data would effectively provide a handle on which climate models are best able to reproduce particular features of actual climate, and hence would offer the potential to reduce the uncertainty in future scenarios by downweighting underperforming models.

7. Summary of integrated methodology

Before summarising the overall conclusions and recommendations of the project, we review the overall procedure that has been developed, as well as the supporting material that is available. A complete worked example, illustrating the use of the procedure and the supporting material in the single-site case, has been prepared as part of Work Package 4 and can be found in Report 6.

The steps in the overall procedure have been summarised already in Section 2.3, and can broadly be summarised as:

(1) assemble data
(2) fit models
(3) simulate daily sequences
(4) simulate subdaily sequences if required.

The work required in steps 2 to 4 can all be carried out using freely available software. The main tools required are the GLIMCLIM software package, together with the statistical packages R and WinBUGS. Unfortunately the latter will only run in a Windows environment, although all of the other software is essentially open source and can be run under most operating systems. The required packages can all be downloaded by following links on the project web pages. In addition to these packages, some intermediate processing is required to convert the output from each step of the procedure into a format suitable for input into the next step, and to convert the rainfall, atmospheric and climate model data into the required format at the outset. Some example scripts and executables (in R and FORTRAN) are provided on the web site to assist with this.

To give an overall impression of what is required operationally to use the methodology, we now describe what is involved in carrying out each of steps 2, 3 and 4 in Section 2.3. Full instructions are given in Report 6.

Step 2a: fit GLMs for rainfall occurrence and amounts. This is achieved by running the “fit_logi.exe” and “fit_gamm.exe” executables from the GLIMCLIM software package. These will calibrate the models against a rainfall record with associated atmospheric variable information (which should have been collated in step 1 of Section 2.3). The structure of both occurrence and amounts models is defined to GLIMCLIM via model definition files; templates are available from the project web site. It should not be necessary to alter these templates, since they define model structures that appear to be valid at a wide range of sites in England and Wales. The GLIMCLIM software produces a range of diagnostics after fitting each model; assuming that these indicate an adequate fit, this part of the procedure should take at most 15 minutes.

Step 2b: fit a hierarchical time series model to the outputs from several climate models. This is achieved by running an R script that is linked to WinBUGS. The necessary R and WinBUGS code are available from the project web site. The fitting of hierarchical models is computer-intensive, and can be expected to take a couple of hours.

Step 3: simulate daily rainfall sequences using GLIMCLIM. This is achieved by running the “simrain.exe” executable, in conjunction with model definition files produced by GLIMCLIM in step 2a and with specific sequences of atmospheric variable data – which could be derived directly from climate models, or from the hierarchical time series model from step 2b. The time-consuming part of this step is the preparation of the atmospheric variable sequences; once these have been assembled, simulation of (say) 100 30-year sequences of daily rainfall will usually take less than 15 minutes on a modern PC.

Step 4a: calculate statistical properties of the GLM simulations and use these to reconstruct the corresponding subdaily properties. This can be achieved relatively straightforwardly using scripts that are available from the project web site.

Step 4b: fit a Poisson cluster model separately to each month of the simulation period. This is achieved using R scripts and fitting routines, and is probably the most computationally demanding part of the entire procedure (for a 30 year simulation period, this requires the fitting of 360 separate models, which can easily take 12 hours). Practitioners may prefer to fit a single model for each month of the year, which will reduce the load by a factor of 30.

Step 4c: simulate as many realisations as required from the fitted Poisson cluster models. This can be achieved using simulation software that is available on request from the authors.

At present therefore, to carry out each of the above steps individually is reasonably straightforward; indeed, apart form step 4b it is likely that less time will be spent in carrying out these steps than in the intermediate processing of results. Substantial gains in efficiency would result from the availability of software tools for automating the entire procedure and thereby reducing the need for manual intervention. Within the resources available during the project however, it was not possible to develop such tools.

8. Conclusions and recommendations

8.1 Scientific conclusions

The main scientific conclusions from the project are as follows:

1. Differences between climate models are a major source of uncertainty in future rainfall scenarios. In Figure 8 for example, the range of simulated annual rainfalls accounting for climate model uncertainty is roughly twice as large as that based solely on the output from the Hadley Centre model.

2. The daily rainfall generation methodology developed in project FD2105 is suitable for downscaling climate model outputs to single or multiple sites. The main limitation of the methodology at present is the underestimation of summer rainfall extremes.

3. It suffices to use monthly series of large-scale atmospheric variables to drive simulations of daily rainfall; some gains are possible by using daily sequences instead, but these are relatively small.

4. It is possible to reconstruct properties of subdaily rainfall sequences from those of daily sequences, by exploiting scaling relationships that are valid over a wide range of atmospheric conditions and hence may be expected to hold in a moderately changed climate. This provides a means of calibrating models for the generation of subdaily rainfall sequences.

5. Under the SRES A2 emissions scenario, there will be a tendency for summers to become drier and winters wetter in southern England. This is associated with a decrease in numbers of storms in summer, but a general increase in the intensity of rainfall within storms. This increase in intensities may lead to an enhanced risk of flooding associated with short-duration rainfall events. These projected changes agree in qualitative terms with those obtained using other, quite different, methods.

6. The deficiencies of the daily rainfall models with respect to summer extremes are accentuated in the subdaily models, although these models still provide useful qualitative information regarding the mechanisms underlying changes such as those described in the previous paragraph.

7. The multi-site subdaily simulation methodology from project FD2105 can be applied in a downscaling context, by disaggregating multi-site daily simulations from a GLM. This methodology relies on the initial disaggregation at a single site using the HYETOS software; this itself provides an alternative means of generating single-site subdaily sequences.

8. It has been demonstrated that a hierarchical model provides a convenient and feasible means of combining information from different climate models, in such a way as to represent climate model uncertainty in a logically consistent manner.

8.2 Recommendations for practitioners

For practitioners, the most important message to emerge from this work is the need to consider information from more than one climate model when carrying out climate change impact assessments. Failure to do so will result in substantial underestimation of uncertainty. This is true regardless of the method used for rainfall scenario generation.

Apart from this 'headline', the following recommendations can be made:

1. The GLIMCLIM software developed in project FD2105 is suitable for the generation of single- and multi-site sequences of daily rainfall incorporating scenarios of climate change. Single-site generation is particularly straightforward, since template model definition files are available that can be applied easily at any location in England and Wales.

2. The properties of daily rainfall simulations from GLIMCLIM are generally in good agreement with observations. Interannual variability is well represented, as are winter extremes and seasonal totals. This means that the simulations are potentially appropriate for application to water resource management problems, and for the study of winter flooding. However, the simulations tend to under-represent the magnitude of summer extremes and therefore, at the present stage of development, should be treated with caution when assessing flood risk from short-duration events in summer.

3. For subdaily rainfall simulation at a single site, the methodology developed in this project is potentially powerful, but it is also computationally intensive and needs further testing before we can be confident that it is applicable throughout the UK. Moreover, at the time of writing the software is written in such a way that manual intervention is required at various stages in the process. In the short term therefore, practitioners may prefer to disaggregate a daily sequence using an alternative method such as HYETOS.

4. The methodology for dealing with climate model uncertainty is, we believe, promising. The indications are that it is computationally feasible and that the process of model fitting and simulation can be automated reasonably straightforwardly. However, the work carried out here is preliminary in nature and should be regarded as a pilot study. More experience of the methodology is required before it can be recommended for routine use. In the meantime, a crude way to account for climate model uncertainty is to pool rainfall simulations driven by the outputs from several climate models. These outputs are available as part of the SDSM archive. This is far better than relying on a single atmospheric sequence from one climate model, but will still lead to underestimation of uncertainty.

8.3 Further work

On the basis of the conclusions and recommendations above, the following areas have identified as requiring further work:

1. The daily rainfall simulation model needs some further development, in order to improve the representation of extreme summer rainfalls. This can be done by allowing a seasonally-varying shape parameter in the gamma distributions for rainfall amounts. This will involve a moderate amount of theoretical work and associated software development. It is anticipated that it will lead to a substantial improvement in the reproduction of subdaily extremes using the methodology of Section 4
.
2. The scaling relationships between rainfall properties at different time scales need to be verified further using an extended rainfall data set. A national verification exercise would enhance the credibility of these relationships, and hence that of the subdaily rainfall generation methodology proposed here.

3. More experience is required with the pilot methodology for combining climate model outputs. Further methodological development would also be useful, in particular to incorporate climate model and observational data for the control period. This would potentially reduce future uncertainty, by identifying which climate models are best at reproducing particular features of observed atmospheric time series.

4. It would be useful to improve the accessibility of some of the techniques that have been developed, by connecting some of the software tools so as to reduce the need for manual intervention when implementing the methodology.

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References

Allen, M., Stott, P., Mitchell, J., Schnur, R., and Delworth, T. L. (2000). Quantifying the uncertainty in forecasts of anthropogenic climate change. *Nature*, **407**, 617-620.

Allen, M. R. and Stainforth, D. A. (2002). Towards objective probabilistic climate forecasting. *Nature*, **419**:228.

Chandler, R.E. (2002). GLIMCLIM: Generalised linear modelling for daily climate time series (software and user guide). *Res. Rpt. 227, Dept. Statistical Science, University College London* (http://www.ucl.ac.uk/Stats/research/Resrprts/abs02.html#227).

Chandler RE and Wheater HS (2002). Climate change detection using Generalized Linear Models for rainfall – a case study from the West of Ireland. *Water Resour Res* **38** (10), doi:10.1029/2001WR000906.

Charles, S., Bates, B., Smith, I., and Hughes, J. (2004). Statistical downscaling of daily precipitation from observed and modelled atmospheric fields. *Hydrological Processes*, **18**, 1373-1394.
Coe R and Stern R (1982): Fitting models to daily rainfall. *J. Appl. Meteorol*. **21**: 1024-1031.
Fowler, H. J., Kilsby, C. G., and O'Connell, P. E. (2000). A stochastic rainfall model for the assessment of regional water resource systems under changed climatic conditions. *Hydrology and Earth System Sciences*, **4(2)**:263-282.
Fowler, H.J., Kilsby, C.G., O'Connell, P.E. and Burton, A. (2005). A weather-type conditioned multi-site stochastic rainfall model for the generation of scenarios of climatic variability and change. *J. Hydrol.* **308**, 50-66.
Frei, C., Christensen, J., Deque, M., Jacob, D., Jones, R., and Vidale, P. (2003). Daily precipitation statistics in regional climate models: Evaluation and intercomparison for the European Alps. *Journal of Geophysical Research*, **108**(D3(4124)).
Gelman, A. (2006). Prior distributions for variance parameters in hierarchical models (comment on article by Browne and Draper). *Bayesian Analysis* **1**: 515-534.
Gelman, A.B., Carlin, J.S., Stern, H.S. and Rubin, D.B. (2003). *Bayesian Data Analysis*. Chapman and Hall / CRC Press, Boca Raton.
Giorgi, F. and Mearns, L. O. (2002). Calculation of average, uncertainty range, and reliability of regional climate changes from AOGCM simulations via the "Reliability Ensemble Averaging" (REA) method. *Journal of Climate*, **15**:1141–1158.
Güntner, A., Olsson, J., Calver, A., Gannon, B. (2001) Cascade-based disaggregation of continuous rainfall time-series: the influence of climate, *Hydrology and Earth System Sciences*, 5(2), 145-164
Harris, I. (2004). *Climate scenarios for water resource planning; evaluating GCM products for downscaling regional scenarios*. Technical Report X1-045/2B, Environment Agency.
J.T. Houghton, L.G. Meiro Filho, B.A. Callander, N. Harris, A. Kattenberg and K. Maskell (ed.) (1996). *Climate change 1995: the Science of Climate Change*. Contribution of Working Group I to the Second Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press.Olsson, J. (1995) Limits and characteristics of the multifractal behaviour of a high-resolution rainfall time-series, *Nonlinear Processes in Geophysics*, **2**, 23-29.
Hulme,M., Jenkins,G.J., Lu,X., Turnpenny,J.R., Mitchell,T.D., Jones,R.G., Lowe,J., Murphy,J.M., Hassell,D., Boorman,P., McDonald,R. and Hill,S. (2002) *Climate Change Scenarios for the United Kingdom: The UKCIP02 Scientific Report*. Tyndall Centre for Climate Change Research, School of Environmental Sciences, University of East Anglia, Norwich, UK (http://www.ukcip.org.uk/resources/publications/). 120pp.
IPCC (2001). *Climate Change 2001: the scientific basis* (third report of the Intergovernmental Panel on Climate Change). Cambridge University Press, Cambridge.
Kalnay, E., Kanamitsu, M., Kistler, R., Collins, W., Deaven, D., Gandin, L., Iredell, M., Saha, S., White, G., Woollen, J., Zhu, Y., Chelliah, M., Ebisuzaki, W., Higgins, W., Janowiak, J., Mo, K. C., Ropelewski, C., Wang, J., Leetmaa, A., Reynolds, R., Jenne, R., and Joseph, D. (1996). The NCEP/NCAR 40-year reanalysis project. *Bull. Amer. Meteorol. Soc.*, **77**:437–471.

Kilsby, C. G., Cowpertwait, P. S. P., O'Connell, P. E., and Jones, P. D. (1998). Predicting rainfall statistics in England and Wales using atmospheric circulation variables. *International Journal of Climatology*, **18**: 523-539.

Koutsoyiannis, D. and Onof, C. (2000). HYETOS - a computer program for stochastic disaggregation of fine-scale rainfall (http://www.itia.ntua.gr/e/softinfo/3/).

Koutsoyiannis D and Onof C (2001). Rainfall disaggregation using adjusting procedures on a Poisson cluster model. *Journal of Hydrology*, **246**:109-122.

de Lima, M.I.P., Grasman, J. (1999) Multifractal analysis of 15-min and daily rainfall from a semi-arid region in Portugal, *Journal of Hydrology*, 220, 1-11

Lopez, A., Tebaldi, C., New, M., Stainforth, D., Allen, M., and Kettleborough, J. (2006). Two approaches to quantifying uncertainty in global temperature changes. *J. Climate*, **19,** 4785-4796.

Onof C, Chandler RE, Kakou A, Northrop P, Wheater HS, Isham VS (2000) Rainfall modelling using Poisson-cluster processes: a review of developments, *Stoch. Envir. Res .Risk Assess.* **14**: 384-411.

R Development Core Team (2006). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria (http://www.R-project.org).

M.-L. Segond, C. Onof and H.S. Wheater (2006). Spatial-temporal disaggregation of daily rainfall from a generalized linear model. *J. Hydrol*. **331**, 674-689.

Senior, C.A., Jones, R.G., Lowe, J.A., Durman, C.F. and Hudson, D. (2002) Predictions of extreme precipitation and sea-level rise under climate change, *Phil Trans. R. Soc. London A* , **360**, 1301-1311.

Smith, L.A. (2002) What might we learn from climate forecasts? *Proc. Nat. Acad. Sci. Amer.* **99**: 2487-2492.

Smithers, J., Pegram, G., and Schulze, R. (2002). Design rainfall estimation in South Africa using Bartlett-Lewis rectangular pulse rainfall models. *J. Hydrol.*, **258**, 83-99.

Spiegelhalter, D., Thomas, A., Best, N., and Lunn, D. (2004). *WinBUGS User Manual*. MRC Biostatistics Unit, Cambridge, UK, second edition. Manual and software available from http://www.mrc-bsu.cam.ac.uk/bugs/welcome.shtml **.**

Wheater, H.S. (2002) Progress in and prospects for fluvial flood modelling. *Phil. Trans. R. Soc. Lond. A*, **360**, 1409-1431.

Wheater, H.S., Chandler, R.E., Onof, C.J., Isham, V.S., Bellone, E., Yang, C., Lekkas, D., Lourmas, G. and Segond, M-L. (2005) Spatial-temporal rainfall modelling for flood risk estimation. *Stochastic Environmental Research and Risk Assessment* **19**, pp. 403-416. doi:10.1007/s00477-005-0011-8.

Wheater, H. S., Isham, V. S., Chandler, R. E., Onof, C. J., stewart, E. J., Bellone, E., Yang, C., Lekkas, D., Lourmas, G., Segond, M.-L., Frost, A. J., Prudhomme, C., and Crooks, S. (2006). *Improved methods for national spatial-temporal rainfall and evaporation modelling for BSM*. DEFRA R&D Technical Report F2105/TR.

Wigley, T. and Raper, S. (2001). Interpretation of high projections for global-mean warming. *Science*, **293**(5529).

Wilby, R. L. and Dawson, C. W. (2004). *Statistical Downscaling Model: SDSM version 3.1* (software and user guide). Available from http://www-staff.lboro.ac.uk/~cocwd/SDSM/ .

Wilby, R. L. and Harris, I. (2006). A framework for assessing uncertainties in climate change impacts: Low-flow scenarios for the River Thames, UK. *Water Resources Research*, **42(2)**, doi:10.1029/2005WR004065.
Wilby, R. L., Hassan, H., and Hanaki, K. (1998a). Statistical downscaling of hydrometerological variables using general circulation model output. *Journal of Hydrology*, **205**:1-19.
Wilby, R.L., Wigley, T.M.L., Conway, D., Jones, P.D., Hewitson, B.C., Main, J., Wilks, D.S. (1998) Statistical downscaling of general circulation model output: a comparison of methods, *Water Resources Research,* **24(11)**, 2995-3008
Wilby, R. L. and Wigley, T. M. L. (2000). Precipitation predictors for downscaling: Observed and general circulation model relationships. *International Journal of Climatology*, **20**:641-661.
Wilby, R.L., Charles, S.P., Zorita, E., Timbal, B., Whetton, P. and Mearns, L.O. (2004): *Guidelines for use of Climate Scenarios Developed from Statistical Downscaling Methods*. IPCC Detailed Guidance Note, No. 2. Available from http://ipcc-ddc.cru.uea.ac.uk/guidelines/.
Wilks, D. S. and Wilby, R. L. (1999). The weather generation game: a review of stochastic weather models. *Progress in Physical Geography*, **23(3)**:329-357.
Yang, C., Chandler, R.E., Isham, V. and Wheater, H.S. (2005). Spatial-temporal rainfall simulation using Generalized Linear Models. *Water Resources Research* **41**, doi:10.1029/2004WR003739.

APPENDIX: FIGURES

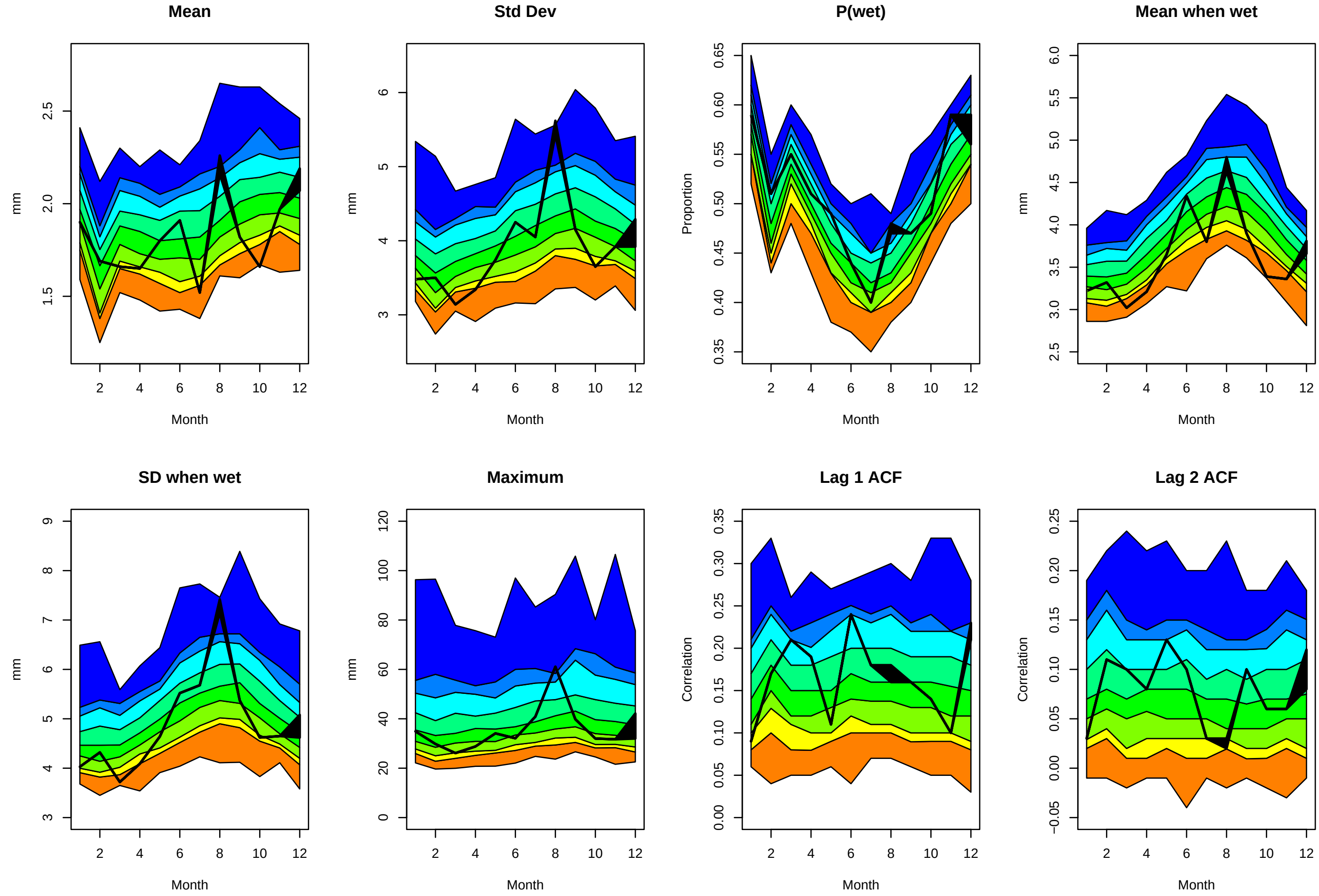

Figure 1 Simulated distributions of monthly summary statistics for daily rainfall at Elmdon. Top to bottom, left to right: mean, standard deviation, proportion of wet days, mean on wet days, standard deviation on wet days, maximum, autocorrelation at lags 1 and 2. The bands correspond to the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentiles and the thick line shows the observed values.

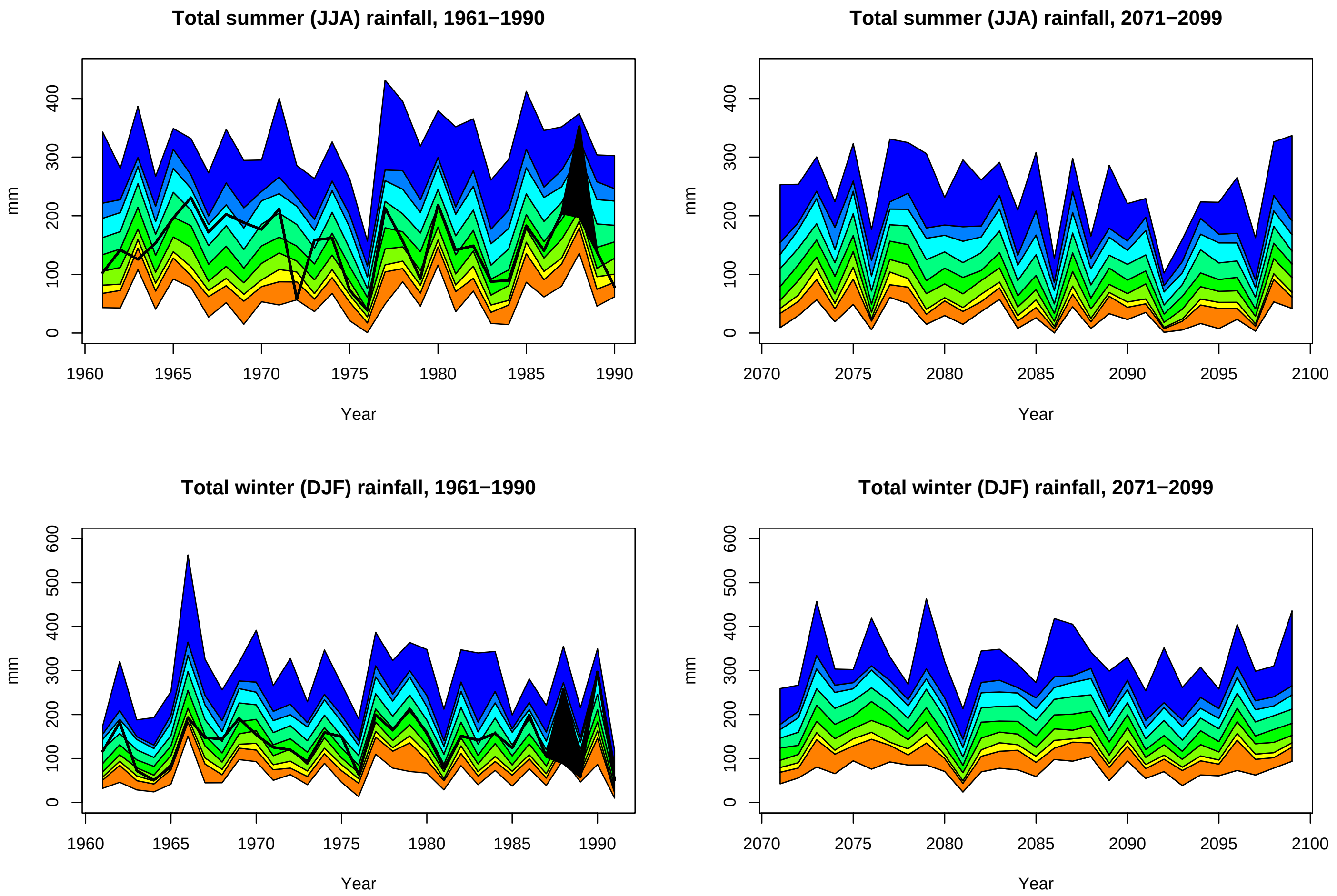

Figure 2 Simulated distributions of total seasonal rainfall at Heathrow. The top plots are for summer (June, July, August) and the bottom plots are for winter (December, January, February). The left- and right-hand columns are for the control and future periods respectively. The future period simulations are conditioned on atmospheric predictors from the HadCM3 GCM.

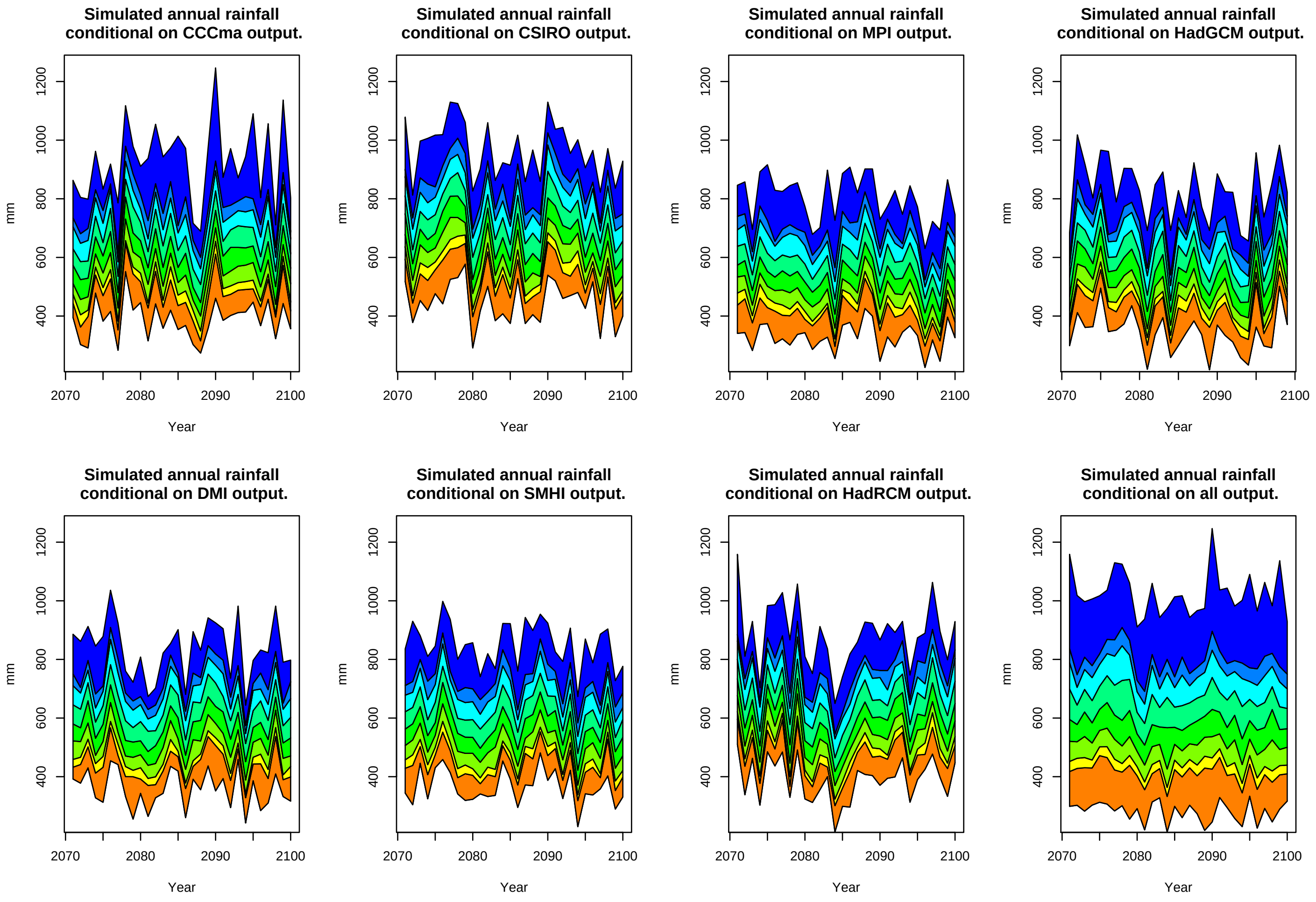

Figure 3 GLM simulated distributions of annual rainfall at Heathrow, 2071-2000. The top four plots are obtained by conditioning on atmospheric sequences from four different GCMS; the first three plots in the bottom row are conditioned on sequences from three different RCMs; and the final plot shows the result of merging the other distributions.

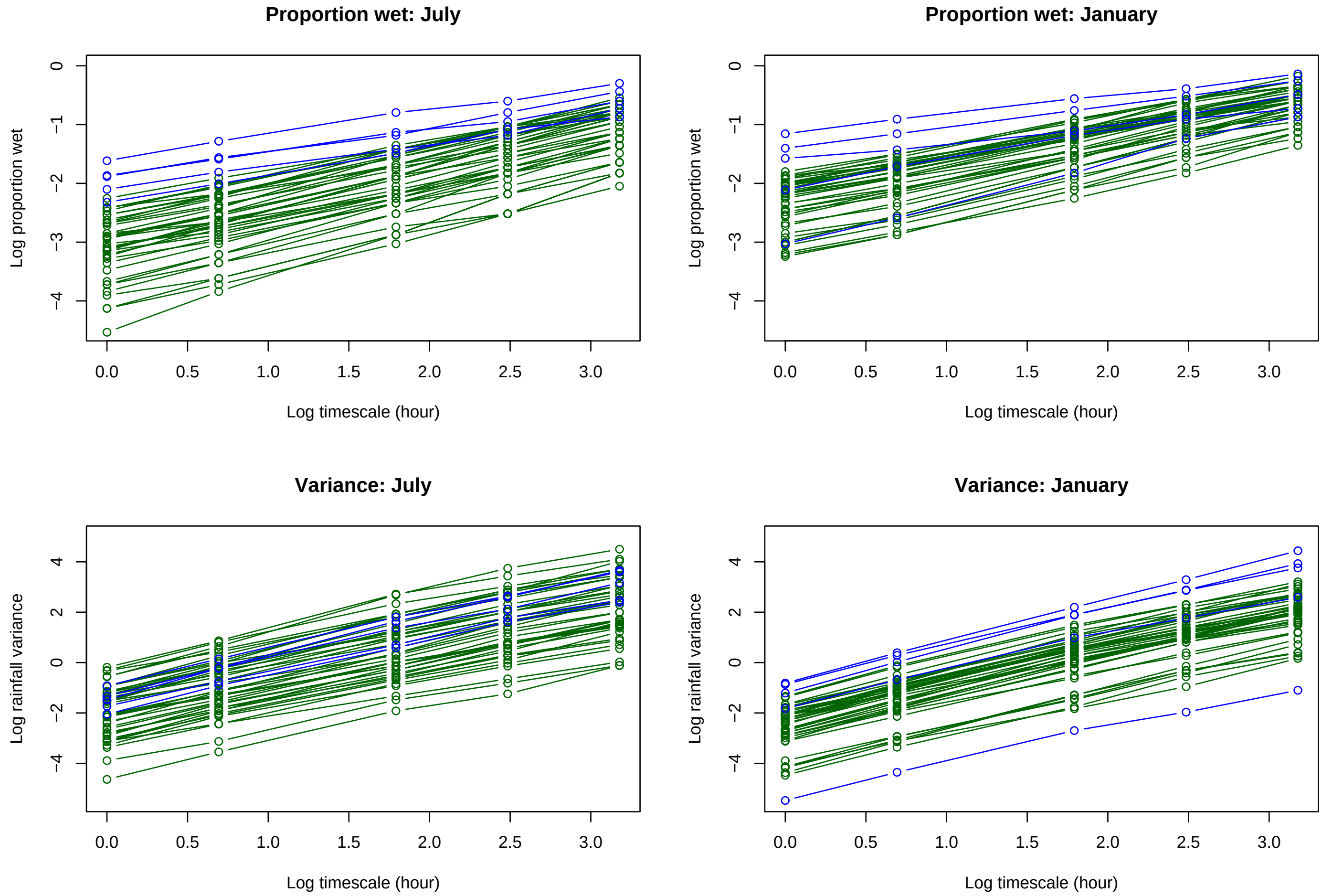

Figure 4 Variation of log(summary statistic) with log(timescale) for Heathrow (green) and Malham (blue) in July (left) and January (right). The top plots are for proportion of wet intervals, and the bottom ones for rainfall variance. See text for further details.

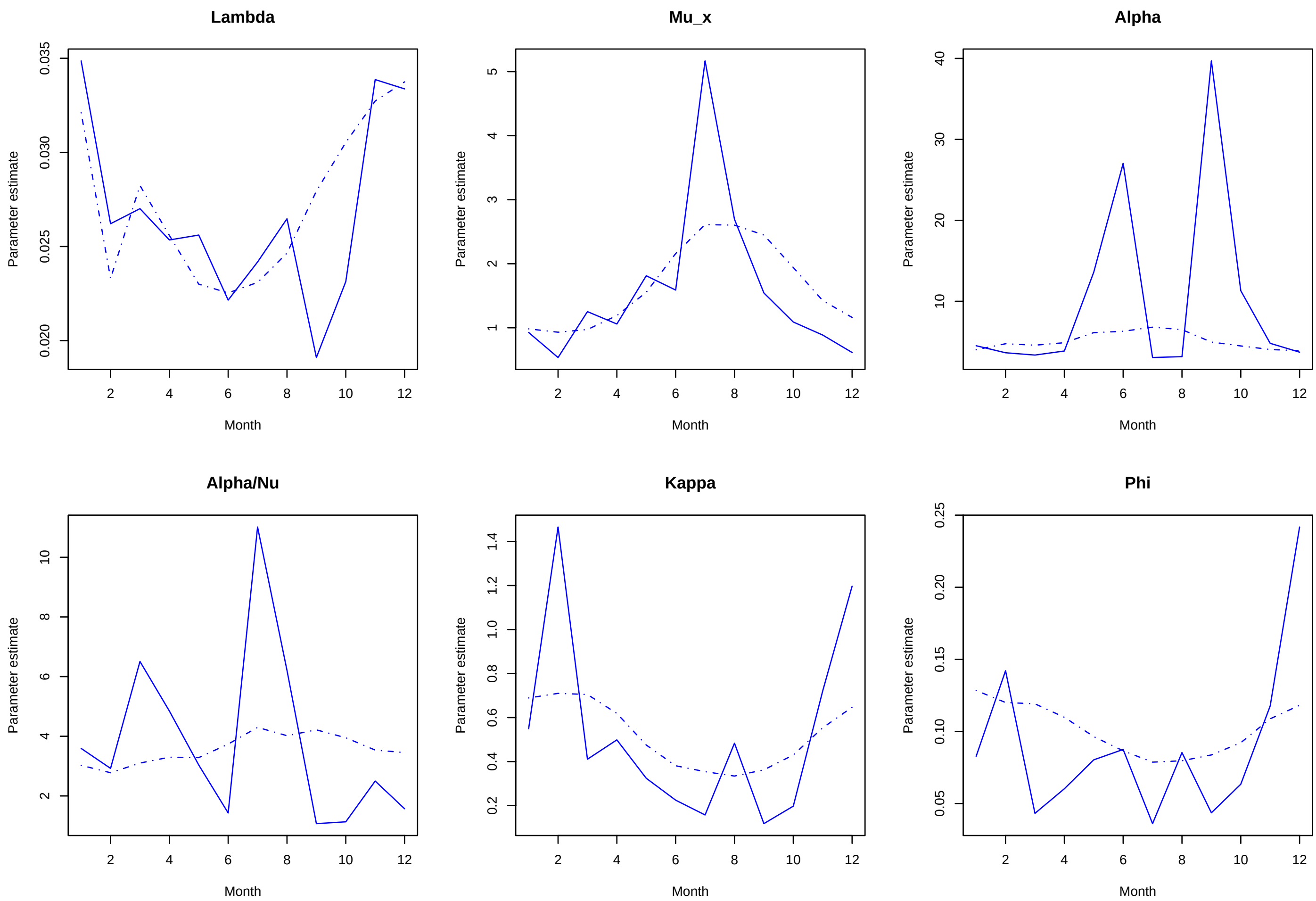

Figure 5 Bartlett-Lewis model parameters derived from observed 1961-1990 rainfall data for Ringway (bold line), and from two hundred 30-year simulations of the Ringway GLM driven by NCEP data (broken line).

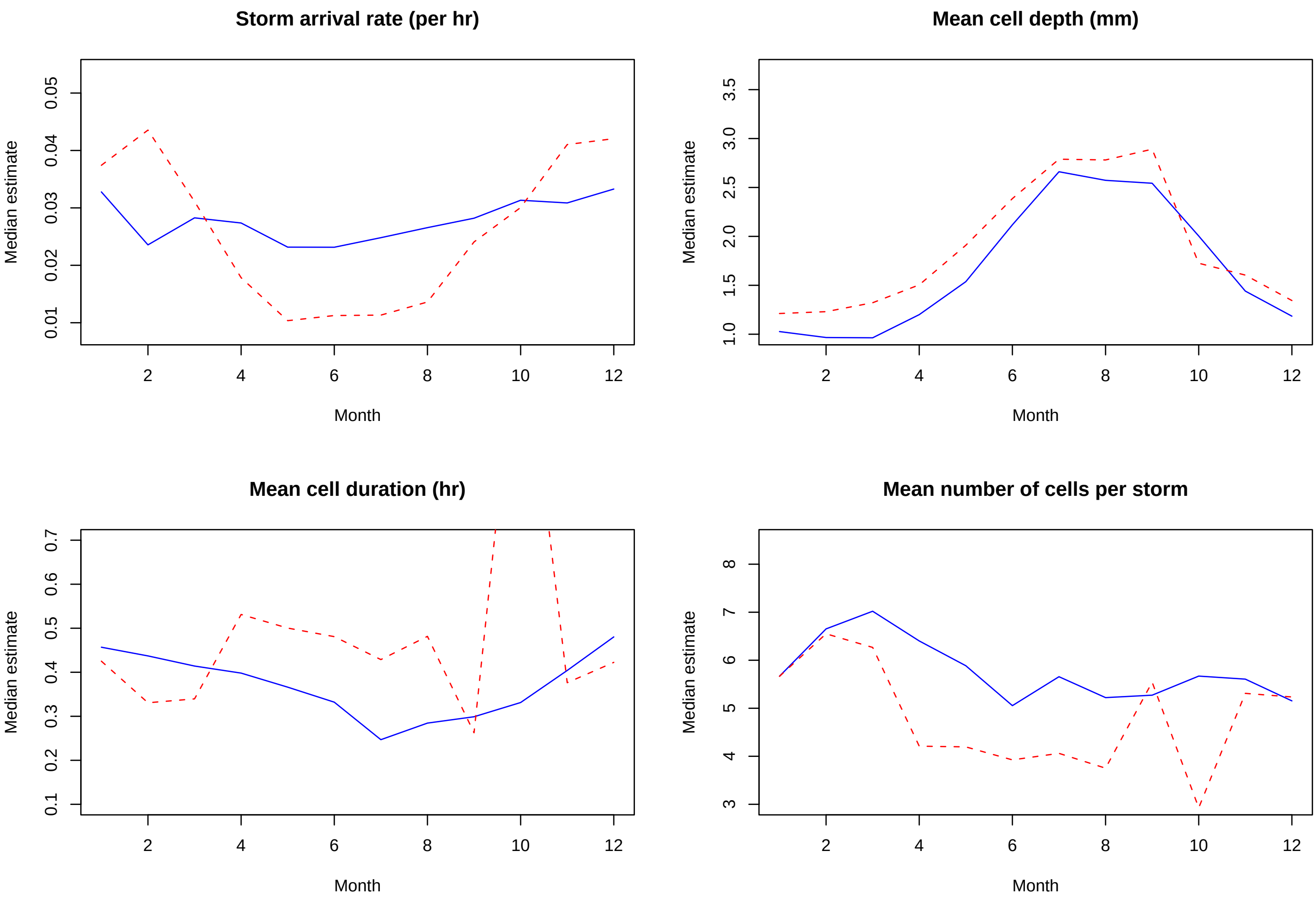

Figure 6 Median parameter values, estimated via strategy 3, by month at Ringway. The blue (solid) line is for 1961-1990, based on GLM rainfall simulations conditional on NCEP atmospheric data. The red (dashed) line is for 2071-2100, based on GLM rainfall simulations conditional on HadCM3 atmospheric output.

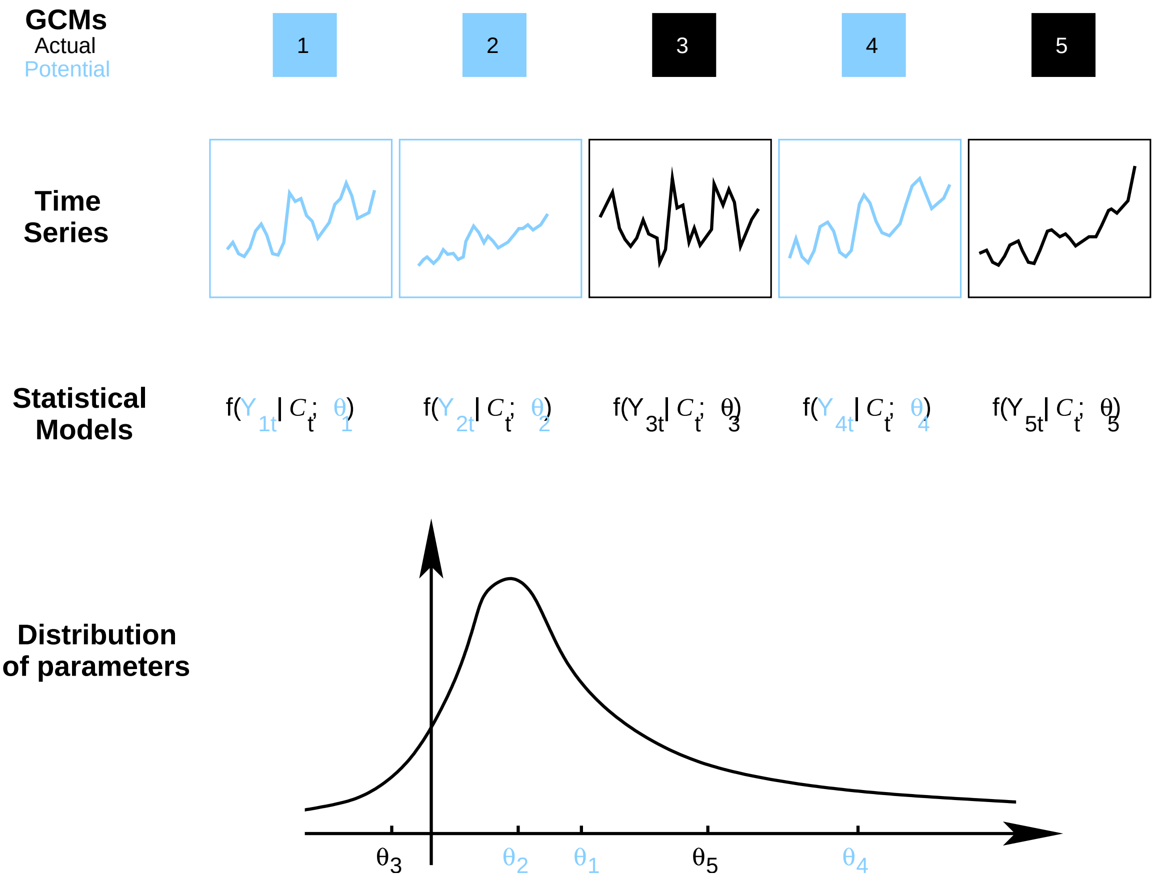

Figure 7 Schematic diagram of the proposed approach for handling climate model uncertainty. See text for details.

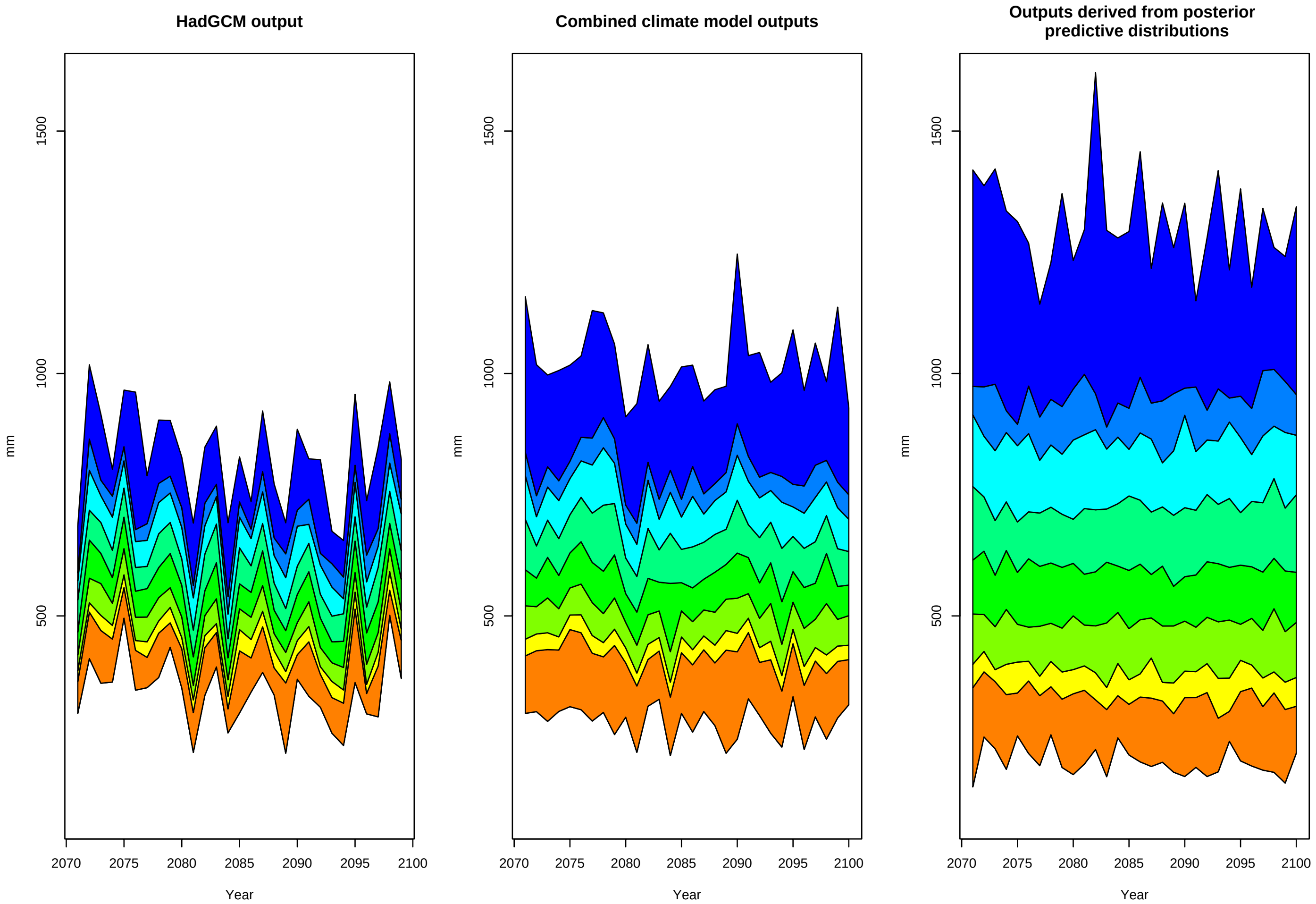

Figure 8 Simulated distributions of annual rainfall totals at Heathrow, 2071-2100. Left: distributions obtained using GLM simulations driven by HadCM3 atmospheric variables. Middle: distributions obtained by combining GLM simulations driven by atmospheric variable sequences from all available climate models. Right: distributions obtained by driving GLM simulations using multiple atmospheric variable sequences from hierarchical multivariate time series model. All distributions are based on 200 GLM simulations.

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